Multimodal Large Language Models for Image, Text, and Speech Data Augmentation: A Survey

RANJAN SAPKOTA*, Cornell University, USA SHAINA RAZA, Vector Institute, Canada MAGED SHOMAN, University of Tennessee, USA ACHYUT PAUDEL, Orchard Robotics, USA MANOJ KARKEE, Cornell University, USA

2025. ACM XXXX-XXXX/2025/3-ART

In the past five years, research has shifted from traditional Machine Learning (ML) and Deep Learning (DL) approaches to leveraging Large Language Models (LLMs), including multimodality, for data augmentation to enhance generalization, and combat overfitting in training deep convolutional neural networks. However, while existing surveys predominantly focus on ML and DL techniques or limited modalities (text or images), a gap remains in addressing the latest advancements and multi-modal applications of LLM-based methods. This survey fills that gap by exploring recent literature utilizing multimodal LLMs to augment image, text, and audio data, offering a comprehensive understanding of these processes. We outlined various methods employed in the LLM-based image, text and speech augmentation, and discussed the limitations identified in current approaches. Additionally, we identified potential solutions to these limitations from the literature to enhance the efficacy of data augmentation practices using multimodal LLMs. This survey serves as a foundation for future research, aiming to refine and expand the use of multimodal LLMs in enhancing dataset quality and diversity for deep learning applications. Paper GitHub: https://github.com/WSUAgRobotics/data-aug-multi-modal-llm.

Additional Key Words and Phrases: Data Augmentation, Large Language Models (LLMs), Generative Artificial Intelligence, Image Augmentation, Text Augmentation, Speech Augmentation, Deep Learning

1 Introduction

Data augmentation is a fundamental technique in machine learning (ML) that enhances the size and diversity of training datasets through the generation of modified versions of existing data samples [1, 2]. This practice uses various transformation functions (TFs), methods like rotating images or changing words, that adjust the original data to produce new variations, as illustrated in Figure 1. Data manipulation experts applied these TFs manually to generate new examples that help train deep learning models more effectively. Specifically, TFs such as image rotation, gaussian blur, zooming in/out (Figure 1) could transform a single image of apples from orchards into multiple orientations, effectively increasing the dataset size for models focused on image processing. Similar TFs for text and audio data, like random insertion and specific audio modifications, broaden datasets for natural language processing (NLP) and audio analysis applications, respectively [3, 4]. These augmentation strategies not only increase the volume of data available for training but also introduce a spectrum of variations that models might encounter in real-world scenarios, thereby enhancing their robustness and generalization capabilities. This foundational practice is depicted through a visual representation in Figure 1 a, showcasing the augmentation of image data with rotated apple images as an example.

Traditionally, data augmentation was performed manually, but with the advent of Long Short-Term Memory (LSTM) networks, it has become a more automated and widespread practice [5, 6]. LSTMs facilitate the automatic generation of synthetic data across various applications, including time series forecasting, natural language processing (NLP), and human activity recognition [7]. This

Authors' Contact Information: Ranjan Sapkota*, Cornell University, Ithaca, New York, USA, rs2672@cornell.edu; Shaina Raza, Vector Institute, Toronto, Ontario, Canada; Maged Shoman, University of Tennessee, Knoxville, Tennessee, USA; Achyut Paudel, Orchard Robotics, Bellevue, Washington, USA; Manoj Karkee, Cornell University, Ithaca, New York, USA, .

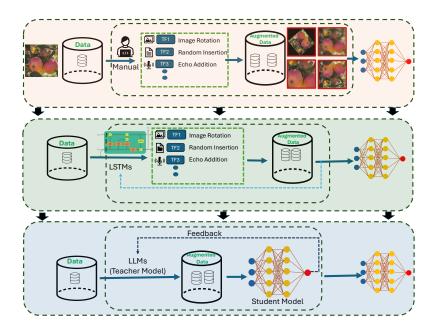


Fig. 1. Evolution of data augmentation techniques (from top to bottom) a) Manual transformation functions like image rotation for training dataset expansion. b) LSTM-based automation generating synthetic data. c) Use of Generative LLMs for advanced, context-aware synthetic data creation, marking a shift to Al-driven data augmentation methods.

shift reduced the reliance on manual data creation, as illustrated in Figure 1 (b), which depicts the transition to LSTM-based data augmentation.

The LSTM-based augmentation became a cornerstone in data-driven fields until the emergence of Large Language Models (LLMs) and generative AI. With the surge in popularity following innovations like ChatGPT, LLMs have begun to redefine data augmentation, particularly by integrating and automating cross-modal synthesis. As shown in Figure 1 (c), this new era leverages the contextual intelligence of multi-modal LLMs to perform data augmentation. These methods also move beyond traditional and LSTM-based methods by providing more sophisticated, contextually aware synthetic data generation across multiple data types.

Data augmentation is crucial for enhancing the robustness and performance of DL models across various domains such as computer vision, NLP, and speech recognition. In computer vision, techniques like random cropping and flipping are normally used to prevent overfitting by promoting generalization across different orientations and expressions [8]. Similarly, in NLP, synonym replacement and paraphrasing help models to generalize across diverse lexical and linguistic formulations, crucial for applications like sentiment analysis and chatbot interactions [2, 9]. In the realm of speech recognition, strategies such as noise injection enable models to perform reliably in noisy environments by simulating various acoustic scenarios [10, 11].

Data augmentation enables model training under varied conditions, like lighting in autonomous driving or medical scenarios in imaging, reducing reliance on costly data collection.[12–15]. It also addresses class imbalance and enhances dataset diversity, which is important for tasks requiring high levels of accuracy in real-world setting, such as machine translation and sound identification [16, 17].

Data augmentation synthetically increases training data, reducing costs, speeding development, and maximizing data resource ROI [2, 18].

Building on the existing foundation of data augmentation methods, the advent of multi-modal LLMs has brought a lot of changes in the field. These models go beyond traditional applications such as machine translation and sentiment analysis, introducing pseudo data generation for classification and dataset enhancement for regression analysis [19, 20]. This shift introduces a transition to more dynamic and functional data augmentation techniques that not only diversify available methods but also deepen our understanding model training and performance [21].

Necessity of this survey While numerous review articles on data augmentation in AI research have explored various techniques, most focus on traditional ML and DL approaches [4–6, 8, 15, 18, 22–30], including GAN-based methods [14, 31–33]. However, these studies often focus on a single modality, such as NLP or image processing. This survey addresses the gap by exploring ML and DL techniques across three modalities, Image, Text, and Speech, while also covering the latest advancements in LLMs and generative AI methods. This survey critically evaluates the diverse methodologies for data augmentation that have emerged over the past five years. In particular, with the rapid advancements and capabilities of LLMs from 2020 to the present, significant transitions in these methods have taken place. We, particularly, focus on the application of multimodal LLMs in data augmentation in generating coherent and contextually relevant synthetic data.

Key Contributions The main contributions of this survey are summarized as follows:

- (1) Coverage of Multi-modality and LLM-Based Data Augmentation Methods: To the best of our knowledge, this is the first survey to comprehensively cover three key modalities in ML research: Image, Text, and Speech. Additionally, it offers an in-depth exploration of the technical methods employed for data augmentation using LLMs across these modalities. We identify and discuss the limitations and challenges inherent in current LLM-based data augmentation techniques for all three data modalities.
- (2) **Ethical AI Research Conduct**: This survey adheres to the principles of ethical AI research, ensuring transparency, fairness, accountability, and integrity throughout the research process. We maintain these standards by carefully collecting literature, respecting copyright laws, and designing the study to be fully reproducible.
- (3) **Analysis, Challenges, and Solutions:** We categorically present the results of our literature research for each modality, highlight the limitations and challenges, and propose potential solutions with the aim of advancing the field.

The survey is structured as follows: Section 2 outlines the *Methodology*. Section 3 provides a brief *Background*, categorizing data augmentation techniques into traditional methods (1990–2010) and ML/DL methods (2010–2020). Section 4, *Results and Discussion*, presents findings for Image, Text, and Speech modalities, analyzing LLM-based augmentation techniques, their limitations, and potential solutions. Finally, Section 6, *Conclusion*, synthesizes insights, discusses future research directions, and highlights the evolution of LLM applications in data augmentation.

2 Literature Review Methodology

To compile a comprehensive and relevant list of papers for our review, we conducted a comprehensive literature review, adhering to established methodology principles [34]. Our search query and extraction methods are detailed below:

2.1 Databases Searched

We conducted an extensive literature review across several renowned academic databases, starting with the DataBase systems and Logic Programming (DBSL) platform¹, which a comprehensive computer science bibliography. Subsequent searches were carried out across Google Scholar, IEEE Xplore, PubMed, ACM Digital Library, Nature, Elsevier, and Scopus, utilizing a color-coded keyword strategy as illustrated in Figure 2 (a).

2.2 Search Keywords

This search yielded 766 papers on "image data augmentation", 336 on "text data augmentation", and 414 on speech-related augmentations using a variety of keywords, including "speech", "audio", "voice", "synthetic data generation", "augmentation techniques", "data preprocessing", "noise injection", "feature transformation", and "data synthesis".

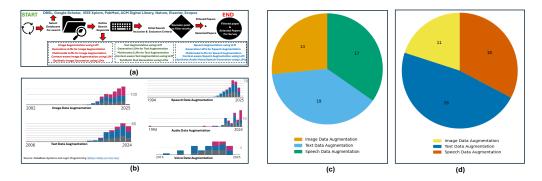


Fig. 2. Survey methodology and results overview: (a) Flowchart of the structured survey method, showing specific search keywords and steps from initial search to study selection; (b) Graph displaying initial search outcomes across the DBSL database, illustrating paper distribution; (c) Pie chart of selected peer-reviewed papers, showing thorough screening; (d) Pie chart of preprints distribution, indicating extensive preliminary research review. Keywords for image, text, and speech augmentation are marked in red, green, and blue, respectively.

2.3 Inclusion Exclusion Criteria

We adhere to ethical guidelines for data search and collection [35], categorizing the historical development of data augmentation into distinct eras. The period from 1990 to 2010 represents the era of traditional methods, characterized by basic techniques. From 2010 to 2020, the focus shifted to advanced machine learning and deep learning (ML/DL) methods. Post-2020 marks the era dominated by LLMs, which have significantly enhanced the scope and effectiveness of data augmentation across various modalities. This historical framework, segmented by technological advancements in image, text, and speech data augmentation, guided our review. The distinctive methods and their evolution in each era were essential to understanding the current landscape shaped by LLMs, as demonstrated by the substantial literature retrieved during the initial search phase, shown in Figure 2 (a).

The screening and selection process identified the most relevant studies for in-depth analysis, as shown in Figure 2 (b), which summarizes the total papers retrieved for image, text, and speech (including audio and voice) data augmentation. These studies formed the basis for understanding

¹https://dblp.uni-trier.de/

the evolution of data augmentation methods across traditional, ML/DL, and LLM-based eras. Further refinement targeted studies utilizing LLMs for data augmentation, detailed in Figures 2 (c) for peer-reviewed journals and 2 (d) for preprints. These figures highlight the rigorous selection process that distilled the most pertinent contributions in the field.

2.4 Quality Assessment

We evaluated the articles using the inclusion and exclusion criteria described earlier. In cases of uncertainty, the paper was briefly reviewed and subsequently included or excluded based on a consensus among the co-authors. The selected papers were then thoroughly reviewed and subjected to a quality assessment using a set of questions. An article was considered eligible for inclusion in our review if it received a "yes" or "partially" response to any of the following questions:

- (1) Does the article present a method for data augmentation in ML/DL/LLM?
- (2) Does the article present a method for data augmentation in image, text, or speech?
- (3) Does the article propose a framework, tool, or methodology?

2.5 Results

In total, our survey evaluated 24 studies focused on image data augmentation from 2020 onwards, which included 13 peer-reviewed papers and 11 pre-prints extensively discussing LLM-based augmentation techniques. For text data augmentation, 45 studies were reviewed, consisting of 19 peer-reviewed articles and 26 preprints. The speech data augmentation modality was represented by 35 studies, encompassing 17 peer-reviewed papers and 18 preprints. Besides, the comprehensive evaluation of the current research landscape, we also highlighted emerging trends and advancements in the application of LLMs.

3 Background

3.1 Historical Context

Data augmentation has undergone significant evolution since the 1990s, as depicted in the upper part of Figure 3, where traditional methods are highlighted in blue, red, and green boxes representing image, text, and speech augmentation respectively. Initially, these traditional techniques, such as image flipping, rotating, and scaling, were employed to enhance dataset variability and robustness. Entering the 2010s, a shift occurred towards more sophisticated ML and DLapproaches, illustrated in the lower part of Figure 3. These ML and DL methods introduced advanced, automated augmentation processes tailored to specific modalities, significantly improving the creation of diverse, realistic datasets that closely mimic real-world complexity. This section provides an overview of the progression from traditional to ML/DL-based data augmentation, setting the stage for our exploration and analysis of multimodal LLM-based data augmentation methods from 2020 onwards.

3.2 Traditional Data Augmentation Methods (1990-2010)

• Image Data Augmentation: Traditional image augmentation methods from the 1990s to early 2000s primarily used geometric and color transformations to enhance ML training datasets, as shown in Figure 3 [36, 37]. These methods improved image quality and interpretability by overcoming the limitations of then-current imaging technology with several innovative techniques. Histogram hyperbolization was introduced to enhance contrast more effectively than standard methods by applying a memory-less nonlinear transformation tailored to human brightness perception [38]. Additionally, non-recursive techniques that utilizes local statistics were developed for noise filtering and contrast enhancement, ideal for

real-time applications [39]. Other techniques, such as included local histogram equalization and dynamic video gain adjustment for enhancing TV-type imagery in varying lighting [40], shock filters based on nonlinear differential equations for reducing oscillations and enhancing feature recognition [41], and fuzzy set theory to improve image clarity and contrast by manipulating pixel properties [42].

Traditional image data augmentation methods, while pioneering for their time, had limitations that could compromise the effectiveness of augmented datasets. Techniques such as image rotation and flipping were straightforward and computationally light, helping to enhance dataset size and variability, but often at the cost of losing important data or introducing artifacts like empty corners or misleading features for asymmetrical objects [43]. Scaling images to simulate depth perception proved useful for creating scale-invariant models; however, this often led to pixelation and resolution loss when images were enlarged [44, 45]. Color jittering adjusted images to simulate different lighting conditions, but excessive alteration could render images unnatural [46]. Similarly, cropping and Gaussian blurring were employed to focus model attention and simulate blur effects respectively, yet these could remove vital image details or overly simplify textures, potentially undermining model training [47–49].

- Text Data Augmentation: Traditional text data augmentation methods, uch as synonym replacement, random deletion, random insertion, back translation and random swapm have been typically used in the training of language models by introducing lexical and structural diversity. Synonym replacement allows for the substitution of words with their synonyms, which helps models in grasping semantic similarities [50, 51]. However, these replacements are sometimes contextually inappropriate, as synonym databases may not capture nuanced meanings or colloquialisms, which occasionally alter intended sentiments or textual nuances [50–52]. Random Deletion methods that removes words to mimic incomplete information, compelling models to deduce missing context, though excessive use risked omitting essential information and skewing data representation [53-56]. Random Insertion is employed to enhance model robustness by inserting random words into unpredictable positions within the text. This method aims to prepare models for handling unexpected or out-of-context inputs. However, it compromises grammatical integrity and adding irrelevant content, which could muddy the training process [57, 58]. Back Translation is another traditional method to translate sentences into a foreign language and then back to the original language, resulting in subtly different paraphrases. This process was dependent on the quality of the translation systems and was noted for being both time-intensive and computationally demanding, especially for longer texts or rarer languages [59-63]. Random Swap reorganized words within sentences to reduce the model's sensitivity to specific word order, benefiting languages with flexible syntax. However, this could also disrupt the natural flow of text and complicate the learning of language rules [58, 64]. Some of the popular text data augmentation methods during the 1990 to early 2000 are illustrated in upper mid part of Figure 3.
- Speech Data Augmentation: Traditional methods of speech data augmentation have been typicall used for auditory experiences across various applications since the early 1990s. Early studies like Cohen (1993) introduced augmented audio reality by merging computer-generated sounds with natural environments, enhancing telepresence and virtual reality interactions [65]. Other contributions include Brandenburg et al. (1992), who used autogenous fat for vocal cord augmentation, showing improvements in voice quality [66], and Watanabe (1985), who enhanced teleconferencing systems by integrating audio and visual information [67].

Schmandt (1990) also incorporated speech input into window systems, facilitating voice-controlled navigation [68], and Adams (1992) utilized the Lombard effect to increase voice intensity in Parkinson's patients [69].

Challanges: These pioneering methods, while useful, face challanges such as alignment accuracy in synthetic audio with real-world environments, vulnerability to background noise, and substantial computational demands for real-time processing. Throughout the late 1990s and early 2000s, techniques like noise injection, pitch shifting, and dynamic range compression were developed to train robust audio recognition systems capable of operating under varied real-world conditions [70–72]. However, these methods often introduced artifacts, distorted audio signals, or overfitting to specific noise types, highlighting a persistent need for improvement in simulating authentic auditory environments for deep learning applications [72–74].

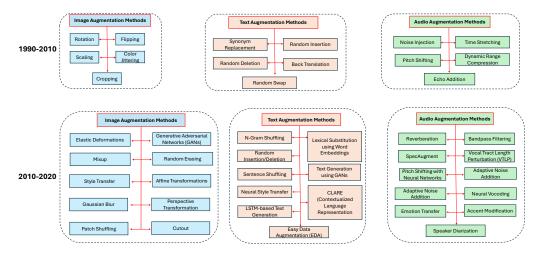


Fig. 3. A comprehensive overview of data augmentation techniques, divided into two main eras: 1990 to 2010, focusing on traditional methods for image, text, and audio augmentation, and 2010 to 2020, highlighting m achine learning and deep learning-based advancements.

3.3 Machine Learning and Deep Learning-based Data Augmentation (2010-2020)

• Image Data Augmentation: Over the past decade, DL/ML based image data augmentation techniques including the methods like rotations, flips, and crops (Figure 3) have been extensively used to train neural networks to be invariant to changes in object orientation, scale, and position, essential in sectors such as medical imaging [15, 75, 76] and autonomous driving [13, 77]. Advanced techniques have also emerged to handle increased task complexity. For instance, elastic deformations and affine transformations including scaling, shearing, and translating are employed to mimic real-world variations and perspective changes. Techniques like Gaussian blur and perspective transformations enhance model tolerance to sensor imperfections and variable viewpoints, while patch shuffling and methods such as cutout or random erasing challenge models by altering image contexts, compelling reliance on less obvious features for predictions [22, 78].

Additionally, innovative augmentation methods have driven substantial progress in fields requiring complex visual processing. MixUp technique blends images and labels to prevent

overfitting by diluting pattern recognition, whereas style transfer and GANs generate stylistically varied or completely synthetic images to enrich training datasets, addressing issues like data scarcity and class imbalance [79, 80]. These methods have found applications beyond traditional realms, enhancing video data robustness in surveillance, adjusting images in agriculture to predict crop health under varied conditions [22, 78], and creating realistic patient data in healthcare for better disease prediction models [81–83].

Challenges: However, despite these advances, challenges persist such as potential image quality degradation from techniques like rotation or scaling [4, 84], which can detrimentally affect training outcomes. Additionally, the complexity of generating sufficiently diverse images that accurately reflect real-world variability necessitates the use of resource-intensive generative models, highlighting the need for continued innovation in augmentation technology [85].

• Text Data Augmentation: From 2010 to 2020, the integration of ML/DL techniques advanced text data augmentation to a great extent. These methods are used to refine the processes that enhance text-based applications like machine translation, information retrieval [7, 27]. The most famous DL/ML based text augmentation methods are illustrated in Figure 3. The period was marked by the application of statistical methods to linguistic databases, greatly improving the handling of textual data [86]. For instance, early work by Fung in 1994, which augmented Chinese dictionaries with statistically collected character groups from corpora, significantly expanded domain-specific and regional word coverage, thereby enhancing natural language applications by enriching the lexicon with words, idioms, and technical compounds [87]. Similarly, Dietterich's 1995 study demonstrated how learning algorithms such as ID3 and backpropagation could improve English text-to-speech systems by enhancing text mapping to phonemes and stresses [88]. Additionally, Rubin's 1987 introduction of the Sampling/Importance Resampling (SIR) algorithm offered a non-iterative alternative for handling missing textual data, advantageous in settings with modest amounts of missing information [89].

Challanges: Despite these advancements, traditional text augmentation methods often struggled to generate contextually relevant data, as synthesized text frequently lacked the accuracy and fluency of human-generated language [7, 27]. Simple techniques like synonym replacement, while initially effective, risked disrupting semantic coherence by introducing contextually inappropriate words, leading to model misunderstandings and reduced performance on downstream tasks [25, 90]. However, the evolution of text augmentation techniques, as illustrated in Figure 3, included diverse methods like n-gram shuffling, which added syntactic diversity, and lexical substitution using word embeddings, which enhanced lexical variety while maintaining semantic content [91, 92]. Advanced approaches like neural style transfer and GANs were developed to produce high-quality, contextually accurate synthetic text, addressing issues of data scarcity and class imbalance in specialized tasks such as medical report generation [59, 60].

• Audio Data Augmentation: The rapid evolution of DL technologies has greatly influenced fields such as NLP, computer vision, and especially speech recognition [23, 93, 94]. These models' effectiveness depends significantly on the availability of large, high-quality datasets [95, 96]. In recent years, the advent of multi-modal LLMs has marked a significant shift in data augmentation strategies, introducing innovative techniques aimed at mitigate data scarcity that enhances the performance of models across various modalities [97]. This advancement is vital for increasing data volume and improving model robustness and adaptability, thereby enabling models to perform reliably under real-world conditions and preventing overfitting [94]. Furthermore, the role of data augmentation extends to supporting ethical AI development

by fostering diversity in training datasets, which is crucial for reducing biases and promoting fairness, particularly in sensitive applications [95].

Challanges: Audio data augmentation poses unique challenges, particularly in replicating authentic sound environments, which are critical for developing effective speech recognition systems [98, 99]. Traditional simple methods like noise addition often fall short of capturing the complexity of real acoustic environments [100]. Moreover, the lack of diverse and high-quality training samples across various languages and dialects significantly hampers the capability of these systems [24]. Addressing these challenges necessitates the development of more sophisticated and rigourous data augmentation methods that can generate realistic and contextually appropriate synthetic audio data. These advanced methods are essential not only for enhancing the performance of speech recognition systems but also for ensuring they are adaptable and effective across different acoustic and linguistic contexts.

4 Literature Review and Comparative Analysis

In this section, we present the results of our literature review.

4.1 LLM-based Image Data Augmentation

4.1.1 Process overview. Image data augmentation represents a complex, multi-step process designed to significantly enhance machine learning models by diversifying the training datasets [8, 101]. Initially, the process starts with Image Encoding, where raw images are converted into a computable format, typically using a vision encoder to distill essential visual information into feature vectors. This step is crucial for preparing images for further processing, as seen in studies like those by [102], where image-text contrastive learning is utilized.

Following the encoding, Prompt Generation involves the LLM generating a textual description of the encoded image. This textual prompt accurately reflects the image's content and serves as a bridge to the next augmentation steps [103]. Augmentation Instruction Generation then takes these descriptions to create detailed transformation instructions. For instance, DALL-E [103] uses these prompts to generate synthetic images that closely mimic the textual description, enhancing datasets with varied visual representations.

The generated instructions are translated into executable code during the Natural Language to Code Translation step. This code is applied to the original images in the Code Execution phase, effectively implementing the desired augmentations. This step is exemplified in the work by [102], where augmented images are created to enhance disease identification accuracy in cassava leaves. Subsequent to the transformation, the Quality Assessment phase ensures the augmented images meet high-quality standards, crucial for maintaining the natural appearance and utility of the images in training scenarios, as noted by [104] in their work on breast cancer diagnosis. Metadata Generation follows, documenting the augmentation details, which is essential for reproducibility and further analytical work [105].

Finally, Dataset Integration incorporates these enriched images and their metadata into larger datasets. These datasets provide a robust training environment that exposes machine learning models to a wide array of visual scenarios, significantly improving their real-world applicability. This integration process is particularly emphasized in studies like those by [106], where augmented datasets help enhance diabetes management. Each of these steps, depicted in Figure 4 (right side as steps), highlights the technical process of LLMs in image data augmentation for advancing AI capabilities in various domains. For example, the integration of LLMs in medical image analysis by [106] and in agricultural applications by [102] showcases the transformative impact of these advanced data augmentation methods, enhancing both the diversity and the quality of datasets for complex visual recognition tasks.

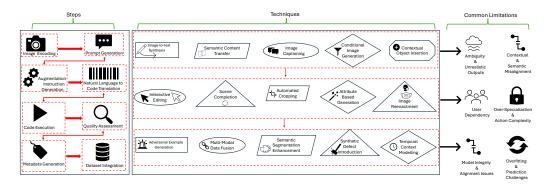


Fig. 4. LLM based image data augmentation: showing the technical aspect of how image augmentation using LLM is performed, the techniques of augmenting images using LLM and their limitations

In the domain of medical diagnostics, LLM-based image data augmentation has shown remarkable utility, particularly in enhancing the accuracy and efficiency of disease detection and treatment monitoring. For example, the Med-MLLM by Liu et al. [107] leverages unlabelled data for radiograph representation learning, significantly boosting diagnostic capabilities in visual and textual analyses. Similarly, the DeepDR-LLM model introduced by Li et al. [106] incorporates advanced lesion segmentation and diabetic retinopathy grading techniques to improve primary diabetes care. Additionally, MISTRA by Jindal et al. [108] utilizes variational autoencoders combined with multimodal fusion techniques to detect and classify medical images with high precision, demonstrating the potential of LLMs to revolutionize medical imaging and diagnostics. Table 1 provides a detailed overview of multimodal LLMs in image data augmentation from the erecent published publications, illustrating the diverse applications across different domains. Additionally, similar detailed information on LLM-based image data augmentation, focusing on the innovations and outcomes from recent peer-reviewed work, is systematically tabulated in Table 4(Refer to Appendix section), further enriching the understanding of how these advanced models are applied in practice.

- 4.1.2 Methods and Techniques. Figure 4 in the middle section comprehensively outlines fifteen diverse techniques of LLM-based image data augmentation identified in our survey, each leveraging the unique capabilities of LLMs to enhance, manipulate, and generate image data, as detailed below
 - Image-to-text Synthesis: Recent advancements in image-to-text synthesis have harnessed the capabilities of LLMs to bridge the gap between visual content and textual descriptions, thereby enhancing the contextual richness of generated images. For instance, the DF-GAN model, introduced by [118], simplifies the generative process through a streamlined one-stage architecture, focusing on improving text-image semantic consistency. This is achieved through innovative components such as a Target-Aware Discriminator and a deep text-image fusion block, which ensure that generated images closely align with their textual descriptions, offering a marked improvement over traditional multi-stage generative adversarial networks. Similarly, [119] employs rich human feedback to refine image generation in response to textual prompts. This method leverages human annotations to identify and correct areas where generated images do not accurately reflect the text, using these insights to train a multimodal transformer that adjusts the generative process, thus enhancing the fidelity and relevance of the output. Additionally, [120] tackles the challenges posed by diffusion models in maintaining fidelity to complex text prompts, by introducing novel loss functions that

Table 1. Survey of Multi-modal LLMs in Image Data Augmentation (Peer Reviewed Papers)

LLM Name	Domain	Data Augmentation Method	Key Insights
DALL-E [103, 109– 111]	Agriculture	Synthetic image generation	Enhanced apple detection with YOLO models; challenges in differences arising from generated images with real-world conditions.
LLM-PTM [112]	Healthcare	Text generation for patient-trial matching	Improved trial-patient matching accuracy; privacy concerns with sensitive healthcare data.
ITIMCA [102]	Agriculture	Image-text fusion, contrastive learning	Improved cassava disease detection under limited data; dependent on high-quality multimodal inputs.
LLM SAM [104]	Healthcare	Dual contrast learning, mask generation	Enhanced breast cancer diagnosis; reliant on high- quality histopathological images.
Generative Models [105]	Robotics	Neural networks for pathfinding	Outperformed traditional pathfinding methods; requires comprehensive training data.
MISTRA [108]	Social Media	Text-image fusion, multimodal detection	Detected misogynous memes with high Macro-F1 scores; challenges in aligning multimodal data inputs.
DeepDR-LLM [106]	Healthcare	DR screening with transformers	Improved diabetes care and DR screening in low- resource settings; integration with clinical work- flows is complex.
Med-MLLM [107]	Healthcare	Multimodal representation learning	Enhanced clinical decision-making with unlabeled radiograph data; scalable for pandemics but limited by rare disease datasets.
Kartezio [113]	Biomedical Imaging	Genetic programming for segmentation	Achieved precision with fewer training instances; complements deep learning but struggles with broader imaging tasks.
ViGPT2 [114]	Healthcare	Vision Transformer, GPT-2 integration	Improved medical image analysis and reporting; dependent on high-quality images and extensive computational resources.
MLLM4Rec [115]	Recommendation Systems	Multimodal learning with prompts	Boosted recommendation accuracy using image and audio data; computationally intensive fine-tuning.
DALLMi [116]	NLP	Semi-supervised domain adaptation	Addressed domain shifts in multi-label classifica- tion; limited by label imbalance and computational demands.
CNN & GPT-3 [117]	Legal	Pseudo-label generation	Improved legal overruling predictions; reliant on pseudo-label quality and computational resources.

guide the image synthesis process more precisely, ensuring that the generated visuals are not only high in quality but also contextually appropriate.

• Semantic Content Transfer: Semantic Content Transfer is another pivotal technique in LLM-based image data augmentation, effectively infusing semantically relevant content into images to boost the robustness and generalizability of machine learning models. The SemAug method, discussed by [121], exemplifies this approach by dynamically incorporating contextually appropriate objects into existing images, which enhances object recognition models without the need for extensive contextual analysis. This method significantly improves model generalization capabilities as demonstrated on standard benchmarks like Pascal VOC and COCO. In a similar vein, DALDA, introduced by [122], integrates semantic information through a sophisticated fusion of LLMs and Diffusion Models (DMs), utilizing enhanced text prompts and adjusted guidance weights to maintain semantic integrity while increasing dataset diversity. This method is particularly effective in scenarios with limited data, demonstrating its utility in enhancing image diversity while preserving semantic accuracy. Furthermore, [123] explores the innovative use of Semantic Imagined Experience in robotics, where text-to-image diffusion models are employed to project robots into varied scenarios through augmented visual data, significantly enhancing their operational adaptability in real-world tasks.

• Image Captioning: Image Captioning for Augmentation represents a significant stride in utilizing LLMs to generate detailed, contextually aligned image captions. The FuseCap technique by [124] innovatively combines machine vision insights with LLM outputs to generate enriched captions that capture overlooked details, thereby improving the training accuracy of visual-language models. This method enhances the detail and accuracy of captions, proving particularly effective in complex image-caption tasks. Additionally, [125] introduces a novel approach that preserves semantic consistency between image-caption pairs through text-conditioned image modifications and advanced data augmentation techniques, such as pixel-level masking. This method ensures that the augmented pairs maintain their semantic linkage, thereby improving the efficacy of grounding-based vision and language models. The benefits of these advancements are further underscored in the study by [126], where image embeddings are synthesized from captions using LLMs and image generation models, showcasing a novel pathway to enriching training datasets without relying heavily on human-labeled data.

- Conditional Image Generation: Conditional Image Generation using LLMs has significantly advanced, allowing for the generation of contextually rich and detailed images to enhance the capabilities of generative models. For example, Koh et al. [127] introduced a method that combines pre-trained image encoders and decoders with text-only LLMs by mapping their embedding spaces, enabling the generation of images conditioned on complex and interleaved text and image inputs. This innovation surpasses traditional models in tasks requiring detailed language understanding. Another noteworthy contribution is from Li et al. [128] with UNIMO-G, a multimodal conditional diffusion framework that excels in generating images from both textual and visual prompts. This framework distinguishes itself by using a Multimodal LLM that encodes mixed inputs and a denoising diffusion process tailored to these complex inputs, demonstrating effectiveness in generating detailed images that purely text-driven models often overlook. Furthermore, Jung et al. [122] discussed DALDA, a framework that combines LLMs with diffusion models to enhance data augmentation under data-scarce conditions, ensuring the generation of semantically consistent images that remain relevant to the training needs. These studies collectively underscore the significant progress in conditional image generation, offering robust solutions for diverse and challenging scenarios.
- Contextual Object Insertion: Contextual Object Insertion in image data augmentation has seen innovative applications through LLMs, enhancing object detection and generalization capabilities of models. SemAug, introduced by Heisler et al. [121], calculates and places new, contextually relevant objects into images, improving model generalization without the need for a context network and demonstrating significant mAP improvements on benchmarks like Pascal VOC and COCO. Similarly, DALDA by Jung et al. [122] integrates LLMs with Diffusion Models to embed novel semantic information into text prompts, maintaining target distribution fidelity while enhancing image diversity. This method proves particularly effective in data-scarce scenarios. Moreover, Yu et al. [123] explore Semantic Imagined Experience in robot learning, using text-to-image diffusion models for data augmentation to robustly perform manipulation tasks in novel scenarios
- Interactive Editing: Interactive Editing with LLMs in image augmentation represents a burgeoning field that combines user input with advanced AI techniques to refine and personalize image outputs. The Visual Editing GPT 3.5 by Sultan et al. [129] utilizes a distillation approach with data augmentation to improve fine-tuning in low-data regimes by 25%, applied effectively in real-time visual editing tasks like color grading. This method demonstrates cost and latency reduction while maintaining high performance. Additionally, ForgeryGPT by Li et al. [130] introduces a novel multimodal LLM for image forgery detection

- and localization, integrating high-order forensics knowledge with explainable AI capabilities. This approach develops innovative training strategies and architecture enhancements, such as the Mask-Aware Forgery Extractor for precise tampering detection and localization, advancing the field towards robust, explainable image forgery analysis.
- Scene Completion: Scene completion using LLMs has become a focal area in enhancing the contextual understanding of images through the seamless integration of missing or incomplete elements. For instance, the Image Augmentation Agent (IAA) developed by Wu et al. [131] uses LLMs and diffusion models to generate high-quality, diverse training images, particularly for semantic segmentation, which includes filling in missing parts of scenes to improve dataset comprehensiveness and quality. This method has shown significant improvements on standard datasets like PASCAL VOC 2012 and MS COCO 2014. Furthermore, the LaB-RAG system by Song et al. [132] enhances radiology report generation by integrating image-derived labels with retrieval-augmented generation, effectively completing scenes with medically relevant data without the need for deep learning model retraining.
- Automated Cropping: Automated cropping leverages LLMs to intelligently crop images, focusing on enhancing the salient parts of an image while maintaining its aesthetic and informational value. This technique is particularly useful in applications where the key features within images vary widely in their placement. For instance, DIAGen introduced by Lingenberg et al. [133] employs Gaussian noise and class-specific text prompts from LLMs to refine the focus of images, ensuring that the most relevant features are emphasized and less important backgrounds are minimized. Similarly, the T2Vid system by Yin et al. [134] applies synthesized video-like samples to improve video understanding, which includes strategic cropping of frames to enhance the model's focus on relevant actions or objects within a dynamic scene.
- Attribute-Based Generation: Attribute-based generation using LLMs focuses on enhancing images by modifying specific attributes or incorporating new ones, thereby increasing the diversity and specificity of image datasets. This technique is crucial for applications requiring high customization or specific attribute alterations. For example, the work by DIAGen [133] not only focuses on diversifying image presentations but also specifically enhances attributes based on class-specific demands, improving classification performance and handling of out-of-distribution samples. Additionally, ForgeryGPT by Li et al. [130] uses multimodal LLMs to detect and localize image forgeries by adjusting image attributes to match forensic profiles, enhancing the detection capabilities. These methods showcase the potential of LLMs to not only generate visually appealing images but also to tailor them to fit specific training or operational need.
- Image Enhancement: Image Enhancement through LLMs involves refining image quality and detail to improve the performance of machine learning models, especially in fields like medical imaging and autonomous driving. For instance, Med-MLLM by Liu et al. [107] develops a multimodal large language model that enhances radiograph representations, aiding in more accurate disease reporting and diagnosis. Similarly, the DeepDR-LLM model by Li et al. [106] integrates LLMs with deep learning for diabetes management by enhancing lesion segmentation and diabetic retinopathy grading. This method significantly improves the clarity and diagnostic utility of medical images in low-resource settings. Additionally, the MISTRA framework by Jindal et al. [108] employs variational autoencoders alongside CLIP and BLIP models for image enhancement, particularly improving the detection and classification of misogynous memes by refining visual cues and text-image congruence.
- Adversarial Examples Generation : Adversarial Examples Generation using LLMs serves as a robust method to test and improve the resilience of AI models against potential exploits.

This method involves creating images that are visually similar to original images but have been subtly altered to deceive AI models. For example, T2Vid by Yin et al. [134] explores the generation of synthesized video-like samples that include adversarial examples to enhance video understanding and model robustness against attacks. Similarly, the DIAGen approach by Lingenberg et al. [133] uses Gaussian noise and targeted attribute alterations to produce images that challenge the model's classification abilities, thereby improving its resistance to adversarial attacks.

- Multimodal Data Fusion :Multimodal Data Fusion in image data augmentation involves integrating information from various modalities, such as text, audio, and images, to create richer and more informative training datasets. This approach is exemplified by the MISTRA system by Jindal et al. [108], which fuses image and text data to improve the accuracy of misogynous meme detection. Additionally, the MM-Instruct by Liu et al. [135] leverages LLMs to generate diverse visual instruction data from image captioning datasets, enhancing the instructional capabilities of large multimodal models. Furthermore, Kartezio by Cortacero et al. [113] introduces a Cartesian Genetic Programming-based strategy for generating interpretable image processing pipelines that effectively integrate multimodal data for biomedical image segmentation.
- Semantic Segmentation Enhancement: Semantic Segmentation Enhancement using LLMs focuses on refining the accuracy with which models delineate and categorize different regions of an image, crucial for applications such as autonomous driving and medical imaging. The Image Augmentation Agent (IAA) by Wu et al. [131] exemplifies this by utilizing LLMs and diffusion models to generate diverse training images, particularly enhancing the model's ability to perform semantic segmentation under weak supervision. This approach notably improves segmentation accuracy on benchmark datasets like PASCAL VOC 2012 and MS COCO 2014 by introducing high-quality, varied training examples that help models better understand complex scene compositions. Additionally, the LaB-RAG system by Song et al. [132] integrates image-derived labels with retrieval-augmented generation to improve radiology report generation, indirectly enhancing semantic segmentation by providing richer context and more detailed labels for medical imaging.
- Synthetic Defect Introduction: Synthetic Defect Introduction through LLMs is a method aimed at creating images with intentionally introduced defects to train models for quality control and defect detection tasks. This method is particularly valuable in manufacturing and quality assurance where detecting subtle defects can be crucial. For instance, DIAGen by Lingenberg et al. [133] uses Gaussian noise and class-specific text prompts to simulate defects in images that help models learn to identify and categorize these defects effectively. Another example is ForgeryGPT by Li et al. [130], which not only detects but also localizes image forgeries by introducing synthetic tampering in a controlled manner. This method enhances the capability of models to discern and react to complex forgery patterns, which are akin to defects in digital media.
- Temporal Context Modeling: Temporal Context Modeling in image data augmentation leverages LLMs to understand and incorporate the temporal dynamics within image sequences, which is essential for tasks such as video analysis and activity recognition. The T2Vid method by Yin et al. [134] enhances video understanding by using synthesized video-like samples that model temporal contexts, thus allowing models to better predict and interpret sequences of actions or events. This method reduces reliance on extensive real video datasets by providing rich, synthesized alternatives that capture essential temporal variations. Additionally, the DALL-M system by Hsieh et al. [136] uses LLMs to generate synthetic clinical

data that includes temporal progressions of medical conditions, improving the predictive capabilities of models in medical diagnostics by understanding disease evolution over time.

- 4.1.3 Limitations and Potential Solutions. The integration of multimodal LLMs in image augmentation introduces several challenges and limitations, which are itemized below and illustrated on the rightmost side of Figure 4:
 - Ambiguity and Unrealistic Outputs: LLM-based image augmentation can face issues with ambiguity and unrealistic outputs due to several underlying scientific reasons. Primarily, LLMs rely heavily on textual prompts for generating images, and if these prompts lack specificity, the resulting images may not capture essential details, leading to generalized or contextually inaccurate representations [118]. Additionally, the inherent limitations of LLMs in understanding complex visual semantics can further exacerbate this problem, as the models might not fully grasp subtle dynamics required for accurate visual depiction [119]. Consequently, this can lead to the generation of images that, while plausible at a superficial level, fail to accurately reflect detailed or scenario-specific characteristics, reducing their applicability in tasks requiring high fidelity to real-world contexts.
 - To address ambiguity and unrealistic outputs in LLM-based image data augmentation, future solutions could involve enhancing textual prompts with more detailed and context-specific descriptions. Implementing a multi-modal training approach, where LLMs are trained not just on text but also on richly annotated visual datasets, could improve the models' understanding of complex visual contexts [28, 29]. Additionally, integrating feedback loops where outputs are evaluated and corrected by humans could refine the models' generative capabilities. Advanced algorithms for semantic parsing could also be employed to better interpret and execute nuanced textual prompts, ensuring that the generated images maintain high fidelity to specified details.
 - Contextual and Semantic Misalignment: Contextual and semantic misalignment presents a significant challenge in LLM-based image augmentation due to the complexity inherent in accurately interpreting and integrating contextual cues within images [124]. LLMs, despite their advanced capabilities, can falter in understanding the intricate relationships and subtleties that define a coherent visual context. This misalignment often results in object placements and enhancements that do not logically fit within the existing scene structure, making them appear out of context or blatantly irrelevant [136]. Such inaccuracies can critically undermine the realism and practical utility of the augmented images, rendering them less effective or even unusable for tasks that require high levels of contextual accuracy, such as in training datasets for AI-driven visual recognition systems. The lack of precise semantic understanding in LLMs thus poses a barrier to creating believable and contextually appropriate visual content, which is essential for applications across various domains that rely on visual data [137].

Addressing the limitation of contextual and semantic misalignment in LLM-based image augmentation can be approached by enhancing the contextual awareness and semantic understanding of LLMs. One scientific method involves training LLMs on a broader and more diverse set of context-rich image-text pairs, which can help the models learn more dynamic interpretations of visual contexts and their corresponding textual descriptions [29, 30]. Additionally, integrating attention mechanisms can enable LLMs to focus on relevant parts of an image in relation to textual cues, improving alignment accuracy. Employing advanced techniques such as contrastive learning could also refine the models' ability to distinguish between contextually appropriate and inappropriate augmentations.

• User Dependency: User dependency poses a significant limitation in the current state of image augmentation using multimodal LLMs due to the crucial role that the quality of input prompts and training data plays in determining the effectiveness of the augmentation process. When these inputs are inconsistent or of poor quality, they can result in augmentations that vary widely in quality, thereby adversely affecting the performance and generalizability of the models [136]. This dependence on user-provided data means that LLM-based augmentation systems are only as good as the information they are given. Substandard or contextually inaccurate prompts may lead LLMs to generate irrelevant or misleading outputs, which not only diminish the utility of the augmented images but also hinder the training of robust AI systems capable of operating effectively in diverse real-world scenarios [137].

To mitigate the limitation of user dependency in LLM-based image augmentation, it is essential to enhance the robustness and contextual understanding of LLMs. One scientific approach is to implement adaptive learning algorithms that can refine their performance over time based on feedback loops. These feedback mechanisms allow LLMs to learn from the outcomes of their augmentations and adjust future outputs accordingly, reducing reliance on initial input quality [28]. Additionally, employing sophisticated preprocessing techniques to standardize and enrich input data can help normalize input quality variations [30, 136]. Advanced natural language understanding (NLU) capabilities can be integrated to better interpret and clarify ambiguous or poorly defined prompts. Finally, augmenting training datasets with a wider range of high-quality, annotated examples can teach LLMs to generate more accurate and contextually appropriate augmentations, even from suboptimal inputs.

• Over-Specialization and Action Complexity: Over-specialization and action complexity in LLM-based image augmentation arise primarily from the substantial computational demands associated with processing large datasets or complex multimodal inputs. LLMs, by design, integrate and analyze vast amounts of data to generate high-quality augmentations. This process often involves deep neural networks and sophisticated algorithms that are computationally intensive and energy-consuming [137]. For applications that necessitate real-time processing, such as interactive media or live surveillance analysis, the latency introduced by these computational requirements can render LLM-based solutions impractical. Moreover, the complexity of actions, which refers to the multitude of steps and computations the LLM must perform to produce a single output, further complicates deployment in constrained or low-resource environments. This complexity not only affects scalability but also limits the potential for broader application of LLM technologies in fields where immediate response and agility are crucial [136, 137].

To overcome the limitation of over-specialization and action complexity in LLM-based image augmentation, it is crucial to optimize the computational efficiency of these models. One approach involves refining model architecture to reduce complexity without compromising performance, such as using lighter neural network layers or pruning redundant parameters . Implementing more efficient algorithms for processing, like quantization or knowledge distillation, can also decrease computational load, enabling faster processing with fewer resources. Additionally, leveraging edge computing can distribute the computational tasks closer to the data source, reducing latency for real-time applications. Furthe, adopting adaptive computation techniques, which dynamically adjust the processing power based on the complexity of the task, can ensure optimal resource utilization and enhance scalability.

 Model Integrity and Alignment Issues: Model integrity and alignment issues present significant limitations in LLM-based image data augmentation due to the challenges of integrating these advanced models seamlessly with existing technological frameworks. LLMs are typically designed to generate or manipulate data based on very complex and often domain-specific training. When integrated into broader systems that were not originally designed with these models in mind, discrepancies can arise between the output expectations and the actual performance of the LLMs [137]. Ensuring that the augmented outputs align with the specific requirements of practical applications involves not only technical adjustments to harmonize the interface between the LLMs and existing systems but also continuous calibration to maintain the fidelity of the outputs. The complexity of these tasks often requires substantial computational resources and sophisticated algorithms to manage the dynamic nature of LLM behaviors, making integration both technically demanding and resource-intensive. This need for high-level expertise and significant computational investment to ensure alignment complicates the adoption of LLMs in diverse operational environments.

Overcoming model integrity and alignment issues in LLM-based image data augmentation can be achieved through several scientific approaches. Firstly, employing modular integration strategies can allow for more flexible adaptation of LLMs within existing frameworks. This involves designing interfaces that can dynamically adjust to the outputs of LLMs, ensuring smoother integration and alignment with application-specific requirements. Secondly, continuous training and fine-tuning of the models on domain-specific datasets can enhance their understanding and performance, thereby improving the consistency and relevance of their outputs. Thirdly, implementing rigorous validation and testing protocols that simulate real-world scenarios can help identify and correct misalignments before full deployment. Finally, leveraging advanced machine learning techniques such as transfer learning can aid in adapting pre-trained models to new tasks or environments more effectively, enhancing their generalizability and utility across various applications.

• Overfitting and Prediction Challenges: Overfitting and prediction challenges are significant limitations in LLM-based image data augmentation, largely due to the models' propensity to reinforce existing biases and learn specific patterns too well. LLMs, when trained on datasets that lack diversity or fail to capture the full complexity of the target domain, might generate augmented data that is too narrowly tailored to the specific examples they have been exposed to. This results in a model that performs well on training data but poorly generalizes to new, unseen data. Scientifically, this issue arises because LLMs, particularly those with vast parameter spaces, are highly capable of memorizing rather than generalizing from input data. The absence of diverse and comprehensive training examples restricts the model's ability to develop robust predictive capabilities, leading it to make decisions based on limited or skewed perspectives, thereby significantly undermining its effectiveness in real-world applications [136].

To address overfitting and prediction challenges in LLM-based image data augmentation, several scientific strategies can be employed. Firstly, enhancing the diversity of the training dataset is crucial. Incorporating a wide range of images from various contexts and conditions can provide a broader base of examples for the LLM to learn from, promoting better generalization to new data. Secondly, implementing regularization techniques such as dropout, L2 regularization, or early stopping during the training process can prevent the model from fitting too closely to the training data. Additionally, employing cross-validation methods can help in assessing how the model will perform on independent data sets. Furthermore, using ensemble methods, which combine multiple models to make predictions, can reduce variance and improve the robustness of the predictions, further mitigating overfitting issues.

Point Cloud Data Augmentation While point cloud augmentation has traditionally relied on geometric, noise-based, or generative methods in ML/DL frameworks, an emerging research

direction involves leveraging LLMs for more context-driven 3D shape manipulation as presented in 5. These new approaches typically combine text-driven prompts or semantic information with 3D generation pipelines, offering a richer way to produce and edit point clouds.

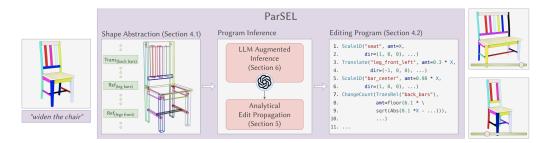


Fig. 5. Conceptual example of LLM-based 3D augmentation. Given a base object, a text prompt could specify modifications like scaling. Adopted from [138]

- Moving Beyond Traditional and ML/DL Methods: Traditional data augmentation strategies focus on generic geometric transformations such as rotation, scaling, translation, and flipping [139, 140], random dropout or noise injection [141], and region-level editing [142, 143]. More advanced deep learning methods use generative models like 3D-GANs [144], VAEs [145], or diffusion models [146, 147] to produce synthetic shapes. These approaches have proven effective, but typically require handcrafted rules or high-level neural networks that do not incorporate natural language feedback. Consequently, the range of possible edits remains constrained by predefined transformations or learned latent spaces.
- Text-Guided Shape Editing and Augmentation: One of the most direct ways LLMs contribute to point cloud augmentation is via text-guided shape editing, where a user or system provides natural language instructions that drive the modifications. Kim et al. [148] introduced a text-to-mesh stylization framework that uses CLIP an early precursor to multimodal LLMs to align a given 3D surface with text prompts (for example, "make it look like coral"). Although focused on meshes, similar text-driven approaches for point clouds have begun to appear. These systems typically rely on LLM-based encoders to parse text instructions and then invoke a generative or editing module to reshape the geometry accordingly, effectively bridging language and 3D shape manipulation.
- Point-E and Shap-E: Diffusion Models with LLM Guidance: OpenAI's Point-E [149] and Shap-E [150] highlight a diffusion-like pipeline for generating 3D point clouds or meshes from textual descriptions. These models often use large text encoders (e.g., from GPT or CLIP families) to interpret prompts such as "a chair with curved legs and a tall backrest," then sample a 3D object consistent with that description. While these systems primarily aim to synthesize 3D shapes from scratch, they also open the door to augmenting existing datasets by generating infinite shape variations with natural language refinements. In principle, one could prompt, "Generate 50 more chairs that have slightly thicker legs and smaller backrests," thereby expanding the range of training samples for a 3D classifier or detector.
- DreamFusion and Zero-1-to-3: Text-Conditioned Neural Fields: A parallel branch of work employs NeRF-like or implicit field representations for text-guided 3D reconstruction. DreamFusion [151] and Zero-1-to-3 [152] both incorporate LLM-based text encoders (often CLIP or a derivative multimodal module) and an optimization process that iteratively refines a neural field to match the text prompt. Although many of these methods yield volumetric

or implicit representations, the resulting geometry can be sampled to produce point clouds. For data augmentation, researchers can systematically vary prompts (e.g., "a slightly longer couch," "a couch with no legs," "a couch with accent pillows") to create a diverse set of shapes without manual 3D modeling.

- Semantic Part Replacement Driven by LLMs: Earlier methods for part swapping in point clouds relied on manual labels or specialized networks that recognized object parts (leg, seat, handle, etc.) [153, 154]. LLMs now offer a more semantic approach, where the model can parse descriptions ("replace the top of this mug with a small dome") and translate them into structured part edits [155]. The system might first map "top of a mug" to a region of a known shape, then retrieve the requested "small dome" geometry from another shape library, assembling them with appropriate scaling. This process can significantly enrich the object varieties seen during training.
- Context-Aware Augmentation for 3D Scenes: Autonomous vehicles and robotics often work in 3D worlds with multiple objects and complex layouts. LLM-driven augmentation can add or modify objects in scene point clouds according to textual commands specifying the scenario. For instance, a user might say, "Add a parked car next to the curb," and the system, guided by an LLM, would select a car model, position it near the curb, and align it with the coordinate system [156]. This approach yields more realistic, scenario-specific data, which helps domain adaptation and robustness. By leveraging an LLM's language-based reasoning, one can generate many scene variations with minimal manual labeling.
- Potential Challenges and Limitations: Although LLM-based approaches promise unprecedented flexibility, they also face unique hurdles. Generating fully realistic and collision-free object placements can be challenging if the LLM's world model is incomplete or if the generative modules are poorly trained. Text prompts can be ambiguous, leading to geometry that misaligns with the intended meaning, particularly if the system lacks strong 3D priors. Another issue involves the computational overhead of large-scale text-driven generation, as well as possible biases in the textual data used to train LLMs. If the model has not been exposed to certain geometric or stylistic concepts, it may struggle to produce them accurately.

In the next few years, researchers are likely to develop more refined pipelines where a language model, a shape retrieval system, and a 3D generative model interact seamlessly. This could involve iterative "conversation-like" steps (e.g., "Make the table thinner," "Shorten the legs," "Move it closer to the wall") akin to prompt engineering, ensuring each new shape version remains semantically valid. There is also a growing push toward multimodal pretraining that unifies 2D images, textual captions, and 3D geometry [157], enabling richer cross-domain data augmentation. Over time, these tools could democratize 3D dataset creation, allowing even non-experts to tailor large point cloud datasets for any target application.

4.2 LLM-based Text Data Augmentation

4.2.1 Process Overview. The process of text data augmmentation using multimodal LLMs can be summarized into eight key steps as illustrated in Figure 6(left side). It begins with text encoding, where raw text data is transformed into a machine-readable format through techniques like tokenization and embedding. Tokenization breaks down the text into manageable units, while embedding assigns these units into a high-dimensional space that reflects semantic relationships [158]. This encoded form serves as the foundation for the LLM to understand and interact with the text. Following encoding, prompt generation occurs where the LLM utilizes the encoded data to generate prompts that direct the augmentation. These prompts define the type of transformations needed, such as paraphrasing or stylistic changes, which guide the subsequent augmentation steps. Next,

augmentation instruction generation takes the prompts to develop specific directives for altering the text [159]. These instructions dictate exact changes like synonym replacement or sentence rephrasing, ensuring the modifications align with the augmentation goals. The process then moves into natural language to task-specific transformations, where these instructions are interpreted and applied to the text, adapting it for specific tasks while maintaining linguistic accuracy [158]. This stage is crucial for ensuring the relevance and applicability of the transformations to the intended training objectives.

Following this, text transformation execution is carried out, where the actual modifications are implemented on the text. This involves sophisticated linguistic manipulation techniques that adjust the text according to the predefined instructions, ensuring the new versions are both varied and contextually appropriate [160]. The sixth step, quality assessment, evaluates the augmented texts against quality standards such as grammaticality, coherence, and task relevance. This evaluation often employs both automated metrics and manual reviews to ensure only high-quality augmentations are retained [161]. Upon successful quality verification, dataset integration occurs, where the augmented texts are systematically compiled into the training dataset. Alongside, metadata generation provides a comprehensive annotation of the modifications applied, including the type and scope of transformations. This metadata is essential for tracking the augmentation impacts and refining future augmentation strategies, thereby enhancing the training datasets' utility and effectiveness in developing robust NLP models[158, 161].

4.2.2 Methods and Techniques. Figure 6 in the middle section comprehensively outlines fifteen diverse techniques of LLM-based text data augmentation identified in our survey as detailed below:

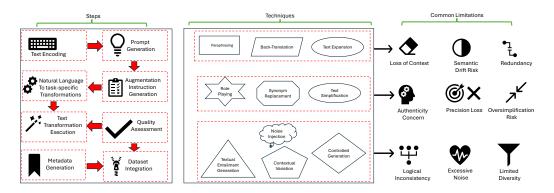


Fig. 6. LLM based text data augmentation : showing the technical aspect of how text augmentation using LLM is performed, the techniques of augmenting text data using LLM and their limitations

• Paraphrasing: Paraphrasing is a critical technique in text data augmentation where the semantics of the original text are preserved while the phrasing and structure are altered. This is achieved through sophisticated LLMs, which analyze and reconstruct text to enhance the richness and diversity of datasets. The method is particularly beneficial in applications requiring nuanced expression alterations without changing underlying meanings, such as personality detection [158] and text classification [160]. For instance, by leveraging semantic and linguistic enrichments, LLMs effectively tailor text data to fit various contexts and styles, thereby improving the robustness and generalization of machine learning models. This approach not only aids in the training of NLP systems but also addresses the challenge of dataset scarcity and bias [132], [177].

Table 2. Survey of Multi-modal LLMs in Text Data Augmentation (Peer Reviewed Papers)

LLM Name/Method & Reference	Domain	Text Augmentation Method	Key Insights
BERT-based TTEC [162]	Fake News Detec- tion	Back-translation and contrastive learning	Enhances detection by 3.1% on Mac. F1 scores; requires larger datasets.
RumorLLM [163]	Fake News Detection	Rumor-specific writing style finetuning	Improves F1 score and AUC-ROC on BuzzFeed and PolitiFact; ethical concerns with textual bias.
LLM-Enhanced Personality Detection [158]	Personality Detection	Semantic, sentiment, and linguistic augmentations	Enhances performance but lacks continuous learning post-deployment.
LLM Mix-Up AAC [159]	Captioning	Caption mix-up augmentation with ChatGPT	Achieves 32.6 SPIDEr-FL score; high computational cost during training.
LLM-Based Civic Issues Detection [161]	Social Media Analytics	Text diversity and imbalance correction	Identifies issues from tweets with 90.9% accuracy; dependent on manual labeling.
ChatGPT-Based DA Enhancement [160]	Text Classification	Rewriting and data generation with ChatGPT	Enhances classification but effectiveness plateaus beyond certain data size.
LA-UCL [164]	Few-shot Learning	Unsupervised contrastive learning with LLM augmentation	Exceeds baseline models but risks overfitting without diverse data.
LLM-Assisted DLP [165]	Dependency Parsing	Multi-level augmentations (word, syntax, discourse)	Boosts Chinese dialogue parsing but struggles to generalize without diverse training data.
TnT-LLM [166]	Text Mining	End-to-end label generation and assignment	Optimizes user intent detection but relies on consistent LLM performance.
LLM-Based Equity Enhancement [167]	Reviewer Assign- ment	Hierarchical data augmentation	Improves reviewer assignment but may generate incorrect domain-specific text.
LLM-PTM [168]	Healthcare	Privacy-aware data augmentation	Enhances patient-trial matching by 7.32%; potential privacy risks.
LLM-PTM [169]	Healthcare	Privacy-aware data augmentation	Increases matching performance but limits direct data usage.
ASM-LMP [170]	Code Summariza- tion	Semantic augmentation for LLM prompts	Surpasses 30 BLEU1 on PHP but lacks generalization across all languages.
CEAN [171]	Event Extraction	Multi-pattern rephrasing with LLM	Achieves state-of-the-art results but faces data noise challenges.
LAMBADA [172]	Sentiment Analysis	Sampling-based data augmentation	Improves robustness on SST-2 but limited by augmentation ratio.
LLM Oversampling [173]	Multiclass Classifi- cation	Generative LLM oversampling	Enhances performance on imbalanced classes but less effective for binary classification.
SK-TOD LLM [174]	Dialogue Systems	Knowledge-grounded data augmentation	Improves task-oriented systems but may not generalize across all subtasks.
Forged-GAN-BERT [175]	Authorship Attribution	Dual augmentation with GAN and Forged Novels Generator	Achieves high F1 scores (0.97, 0.71) but depends on data quality.
OphGLM [176]	Healthcare (Oph- thalmology)	Multimodal data integration with FundusTuning-CN dataset	Superior performance in fundus disease classification but dependent on dataset quality and integration complexity.

• Back-Translation:Back translation involves translating text to a different language and then translating it back to the original language, serving as a powerful method for text augmentation. This technique enriches the linguistic diversity and syntactic variety of text data, crucial for training more resilient NLP models. Studies like [178] utilize back translation to enhance the accuracy of audio description translations in multilingual settings, ensuring the translations retain their original semantic richness across different languages. Moreover, this method supports the improvement of text classification systems by expanding the training dataset with varied syntactical structures, which helps in reducing model overfitting on specific language patterns [179], [180].

• Text Expansion: Text expansion involves elaborating or extending existing text data to create new content that maintains the original context but adds additional descriptive detail. This technique is particularly useful in scenarios where detailed explanatory content enhances model training, such as in medical report generation [132] or environmental informatics [177]. By using LLMs to systematically expand text data, researchers can generate more comprehensive training examples that simulate a wider range of real-world applications. This method not only improves the depth and detail of the datasets but also aids models in developing a better understanding of nuanced contexts and complex scenarios [181], [182]. Additionally, text expansion has proven effective in increasing the robustness of models against overfitting by providing them with a broader array of expressions and contexts, thereby enhancing the generalization capabilities of NLP systems.

- Role Playing:Role playing in text data augmentation involves simulating different perspectives or personas using LLMs to generate diverse responses based on specified roles. This method effectively broadens the scope of conversational models and enhances their ability to handle varied interaction styles, crucial for applications like customer service bots or interactive AI agents. By adopting multiple character roles, LLMs such as those discussed in [132] and [177] can produce more natural and contextually appropriate dialogues, significantly improving user engagement and satisfaction. Role playing also aids in training AI to understand and replicate human emotional nuances, thereby making interactions more realistic and empathetic [182], [161].
- Synonym Replacement:Synonym replacement is a straightforward yet effective text augmentation technique where words or phrases within a text are replaced with their synonyms to introduce lexical diversity without altering the original meaning. This method is instrumental in training NLP models to recognize and process a broader range of lexical variations, enhancing their linguistic adaptability and understanding. Synonym replacement is particularly valuable in tasks like sentiment analysis and text classification, where the robustness of the model against different expressions of the same sentiment or topic is crucial [158], [160]. By integrating synonym replacement, studies such as [183] and [180] demonstrate improved model performance across various text-based tasks by effectively expanding the dataset's lexical field without compromising data quality or contextual relevance.
- Text Simplification: Text simplification involves reducing the linguistic complexity of text while maintaining its essential information and meaning, making it accessible to broader audiences, including those with limited language skills or cognitive impairments. This augmentation technique is crucial in educational technologies and readability enhancements, where complex information needs to be conveyed in simpler terms. Simplification can help in training models to generate more user-friendly content, which is especially important in medical or legal information dissemination [132], [178]. Moreover, by simplifying text, LLMs such as those utilized in [181] and [177] can produce data that supports models in achieving better accuracy in understanding and processing simplified narratives, thus enhancing the overall effectiveness of AI systems in real-world applications.
- Textual Entailment Generation: Textual entailment generation involves using LLMs to create pairs of texts where one text (the premise) logically implies the other (the hypothesis). This form of augmentation is crucial for training models in natural language understanding tasks, such as question answering and information retrieval, where understanding the relationship between text segments can dramatically improve performance. Recent studies like those by [181] and [180] have utilized LLMs to automatically generate large datasets of entailment pairs, which help in improving the inference capabilities of NLP models under various contexts. [132] and [182] also highlighted the use of entailment generation to refine

- models' ability to process and understand nuanced human language, thus enhancing their applicability in real-world scenarios.
- Noise Injection: Noise injection in text data augmentation involves intentionally adding errors or variations to text data, such as misspellings, grammatical errors, or shuffled word orders, to simulate real-world inaccuracies that models may encounter. This technique is crucial for building robust NLP systems that can effectively handle imperfect inputs. Studies by [171] and [173] have shown that training models with noised data can significantly improve their performance in tasks like speech recognition and optical character recognition where input data often contains errors. [164] and [167] further demonstrate that noise injection helps in enhancing the model's resilience against overfitting and improving its ability to generalize from training to real-world application scenarios. By exposing models to a wider array of linguistic variations, noise injection ensures that NLP systems are not only accurate but also adaptable to the imperfect nature of human-generated text.
- Contextual Variation: Contextual variation in text augmentation leverages LLMs to modify a given text's context or to extend its narrative, thus enriching the dataset with diverse linguistic structures and themes. This method is particularly effective in enhancing the model's ability to understand and generate text that varies significantly in style, tone, or context. By integrating studies like [161] and [169], researchers can produce text variations that mimic different dialects, cultural nuances, or domain-specific jargon, broadening the training data's scope and depth. Additionally, works by [158] and [160] have utilized contextual variations to improve the performance of models in tasks that require a deep understanding of context-specific language use, such as sentiment analysis and personalized content generation. This approach not only improves the linguistic versatility of the models but also their applicability across various domains and user groups.
- Controlled Generation: Controlled generation using LLMs focuses on generating text based on specific guidelines or constraints, such as maintaining a certain tone, style, or adhering to predefined content themes. This form of text data augmentation is essential for applications requiring high levels of precision and customization, like marketing content creation or legal document preparation. Controlled generation techniques have been explored in studies like [178] and [177], where LLMs are used to ensure that the generated text meets the specific needs of multilingual translation or tailored content creation. Further, [132] and [184] demonstrate how controlled generation can be applied to create highly targeted training data that enhances the performance of NLP systems within specific functional parameters. This method not only ensures the relevance and applicability of the generated text but also enhances the effectiveness of the training process by aligning it closely with the end-use cases.

4.2.3 Limitations and Potential Solutions.

• Loss of context: Zhao et al. (2024) observed context loss in their study on improving text classification with LLM-based data augmentation [160]. They found that when generating entirely new samples using ChatGPT, the model sometimes produced text that lacked the necessary context for accurate classification. This was particularly evident in domain-specific datasets, where the generated samples failed to capture the detai context of the original data. The loss of context in LLM-based text augmentation can be mitigated through the implementation of fine-tuning strategies that incorporate a mix of relevant and irrelevant contexts, as demonstrated by Yoran et al. (2024) who achieved robustness to irrelevant information with as few as 1,000 training examples [185].

To improve the loss of context in LLM-based text augmentation, it is essential to adopt strategies that enhance the model's ability to retain and understand relevant contexts. One effective approach is through fine-tuning the LLMs on domain-specific datasets. This method enables the models to learn the intricacies and typical patterns within specialized contexts, thereby generating text that maintains the depth and relevance of the original data. Additionally, implementing mixed-context training, can further strengthen the model's robustness against irrelevant information [186]. By incorporating a controlled mix of relevant and irrelevant contexts into the training set, LLMs can learn to discern and prioritize information that is crucial for accurate text generation and classification.

- Semantic Drift Risk The issue of semantic drift was noted by Whitehouse et al. (2023) in their work on LLM-powered data augmentation for multilingual commonsense reasoning [187]. They observed that when generating Tamil text using GPT-4, the model often inserted "uncommon and out-of-context words." For example, the generated text would include phrases that were semantically incorrect or inappropriate for the given context, demonstrating a drift from the intended meaning. Semantic drift can be addressed by employing filtering methods, such as using natural language inference models to assess the relevance of generated content to the original task or domain [185, 188].
 - To minimize the risk of semantic drift in LLM-based text data augmentation for deep learning applications, it is essential to employ advanced filtering and training strategies. Integrating natural language inference (NLI) models can be highly effective. These models assess the logical and contextual relevance of the generated text, ensuring it aligns with the original input's semantic boundaries. This acts as a critical check against the insertion of out-of-context or inappropriate content. Expanding and diversifying the training datasets is another crucial strategy. By incorporating a wide range of linguistic dynamics and diverse contexts, especially in multilingual settings, the LLM can develop a more robust understanding of language patterns. This extensive exposure helps the model better grasp and reproduce the contextual subtleties required for accurate text augmentation. Additionally, implementing adaptive training methods that include feedback loops to continuously refine the model's outputs can further enhance accuracy. This approach allows for real-time adjustments to the model's parameters, correcting deviations and aligning generated content more closely with desired semantic and contextual standards.
- Redundancies and Authenticity Concern: in LLM-generated text were also identified by Whitehouse et al. (2023) [187]. They found that the augmented data often contained "redundant words with the same meaning." An example they provided was the phrase "I will retry to try it again," where the concepts of retrying and trying again are unnecessarily repeated, creating redundancy in the generated text. Redundancies in augmented text can be reduced through the application of model compression techniques like pruning and quantization, which optimize the model's efficiency without significant performance loss, thereby improving the quality and conciseness of generated content [189, 190]. LLM-based text augmentation, while powerful, faces significant authenticity concerns as a key limitation. Research by Silva et al. (2024) [175] and Wu et al. (2023) [191] highlights this issue. Silva's team found that LLMs can produce convincingly human-like texts, creating challenges in authorship attribution, especially in literary contexts. They observed LLMs could generate novels falsely attributed to famous authors or mimic the style of well-known works. Wu's study revealed LLMs' tendency to fabricate information, rely on outdated data, and be overly sensitive to prompts, potentially spreading misinformation and undermining expertise. Both studies emphasize the difficulty in distinguishing LLM-generated content from humanauthored text, with human detection methods proving unreliable

Future research in LLM-based text augmentation could focus on developing advanced filtering mechanisms that leverage natural language inference models and semantic similarity metrics to ensure generated content maintains contextual relevance, semantic coherence, and authenticity, while simultaneously implementing robust verification systems that employ multi-modal analysis to detect and mitigate potential fabrications or misattributions in augmented text

- Oversimplification Risk: Oversimplification Risk in LLM-based text augmentation refers to the potential for generated data to lack the complexity and nuance of real-world examples, potentially leading to reduced model performance on more intricate tasks. This limitation was identified in a study published in August 2024 titled "LLMs vs Established Text Augmentation Techniques for Classification [183]. The researchers found that while LLM-based augmentation can improve downstream classifier accuracy, it may not always outperform established methods significantly. They observed that LLM-generated samples might oversimplify the original text, especially when dealing with complex topics or specialized domains. This oversimplification can result in a loss of important contextual information or subtle features that are crucial for certain classification tasks. The study emphasized the need for careful consideration when using LLM-based augmentation, particularly in domains where detailed understanding is critical for accurate classification. Additionally, the risk of LLMs providing overly simplistic or reductionist assessments, especially in the context of economic policy is highlighted in a recent study [192]. The authors warned that LLMs might generate advice that overlooks important contextual factors, unintended consequences, or distributional effects, potentially leading to suboptimal or harmful decisions if relied upon too heavily.
- Precision Loss and Logical Inconsistency: LLMs often struggle to maintain the semantic integrity of the original text during augmentation. This can result in data that, while varied, might not always be semantically consistent with the source or contextually appropriate, affecting the quality and usability of the augmented data in training models for specific task[193]. The effectiveness of data augmentation heavily relies on the quality of the augmentation instructions provided to the LLM. Poorly defined or ambiguous instructions can lead to augmented data that does not meet the desired criteria or varies significantly in quality across different tasks. A study on ChatGPT-based data augmentation for text classification found that for labels with already sufficient training samples and high accuracy, adding augmented data may introduce noise and decrease performance [160, 194]. Likewise, logical inconsistency in LLM-based text data augmentation poses a significant limitation, impacting the utility and reliability of augmented datasets. Despite LLMs' remarkable capabilities in generating diverse and voluminous textual content, their tendency to produce logically inconsistent outputs when faced with complex input queries can severely undermine the quality of augmented text [195]. This inconsistency often manifests as a divergence in the logical coherence of the text relative to the original material, which is especially detrimental in tasks requiring precise logical structures, such as legal reasoning, academic research, and technical documentation [195, 196]. When employing LLMs for text augmentation, especially in sophisticated domains that require high fidelity to original content meaning and structure, the challenge lies in ensuring that augmented outputs maintain the same logical and factual integrity as their sources [197]. The issue is exacerbated by LLMs' susceptibility to generating responses that, while superficially plausible, may harbor subtle logical errors or misrepresentations known as "hallucinations" in AI parlance . Such errors can mislead downstream applications, lead to the propagation of inaccuracies, and reduce the overall effectiveness of models trained on these datasets.

To overcome precision loss and logical inconsistency in LLM-based text augmentation, it is essential to refine the quality control mechanisms and provide precise, context-specific augmentation guidelines. Enhancing training data with well-annotated, high-quality examples that demonstrate desired outcomes can help LLMs learn to generate more accurate and logically consistent augmentations. Implementing post-generation validation steps, such as semantic and logical coherence checks using rule-based systems or secondary models trained to identify and correct inconsistencies, can further mitigate errors. Additionally, fine-tuning LLMs on a domain-specific corpus before deployment can align their outputs more closely with the contextual and factual demands of specific tasks [160, 195].

• Excessive Noise: Excessive noise in text data augmentation using LLMs refers to the introduction of too much irrelevant or incorrect information during the augmentation process, potentially degrading the quality of the generated data. This can lead to reduced model performance and increased overfitting [193]. Recent studies have highlighted this limitation. Ye et al. (2024) demonstrated that excessive noise in LLM-generated augmented data can compromise the semantic integrity of the original text, leading to decreased name entity recognition (NER) model performance [193]. Similarly, Bolding et al. (2023) [198] observed that while LLMs can effectively clean noisy translation data, they may introduce excessive noise when generating entirely new samples, necessitating careful balance in data augmentation strategies.

To address excessive noise in text augmentation using LLMs, researchers have proposed implementing noise control mechanisms and leveraging LLMs' capabilities for targeted data cleaning [199]. Such approaches include using LLMs to select appropriate noise types for fine-tuning, employing curriculum learning to gradually increase data complexity, and utilizing LLMs to remove specific types of noise while preserving semantic integrity [198, 199].

• Limited Diversity: Limited diversity in LLM-based text data augmentation refers to the challenge of generating sufficiently varied and unique text samples while maintaining semantic consistency with the original data [19]. This can lead to reduced model generalization and reinforcement of existing biases, as the augmented datasets lack the breadth of linguistic expressions, structures, or content necessary to improve model performance effectively [200]. Recent studies have extensively explored this limitation and proposed various strategies to address it, emphasizing the critical need to enhance diversity in LLM-generated text for data augmentation [201].

To address this, recent research has focused on developing strategies to increase the diversity in LLM-generated text. For instance, Cigen et al. (2024) [202] explored how diversity incentives, such as the use of taboo words, chaining techniques, and hints, can enhance lexical diversity in generated paraphrases, ultimately improving downstream model performance. Likewise, future strategies should include diversifying the initial training data, implementing controlled augmentation techniques, and utilizing hybrid models that blend LLMs with adaptive learning methods. Fine-tuning on specialized datasets and applying regularization techniques can help generate more context-specific and varied outputs. Development of diversity-specific evaluation metrics and post-generation refinement processes are also vital. Additionally, monitoring and mitigating biases is crucial to ensure that the augmented data is not only linguistically diverse but also inclusively represents different perspectives, thereby enhancing model robustness and applicability across various domains.

4.3 LLM-Based Speech Data Augmentation

4.3.1 Process Overview. Multimodal LLM-based speech data augmentation can be explained in 7 steps as depicted in Figure 7 (left side). The initial phase of LLM-based speech data augmentation

starts with the meticulous preprocessing of raw audio data. This process involves sampling the audio at a consistent rate, normalizing volume levels to a standard decibel range, and segmenting the speech into shorter clips to facilitate processing efficiency. These steps are critical for ensuring uniformity in data quality, which is vital for effective feature extraction. The feature extraction step converts this standardized audio into a set of features more amenable to machine learning algorithms. Techniques such as extracting Mel-frequency cepstral coefficients (MFCCs) and generating spectrograms are common, as they distill the essential characteristics of speech necessary for recognizing phonetic elements. This extraction process is foundational for enhancing model training and accuracy in diverse acoustic conditions, as demonstrated by Cai et al. ([203]) and reinforced by Dhingra et al. ([204]) in their work on audio-visual deepfake detection and speech de-identification.

The third step involves applying a variety of traditional audio augmentation techniques such as noise injection, time stretching, pitch shifting, and volume adjustment. These manipulations introduce critical variability into the audio data, mimicking real-world audio environments and thus enhancing the robustness of the subsequent models. This approach is crucial for training models to perform reliably across different speaking conditions and noise levels. Studies by Dhingra et al. ([205]) and Ma et al. ([206]) provide evidence that such diversity in training data significantly improves the resilience and accuracy of speech recognition and emotion recognition systems, respectively. The next step is embedding with Multimodal Context and Synthetic Speech Generation, where embeddings are generated using multimodal Large Language Models that integrate both textual and acoustic information, creating a nuanced understanding of the speech context. These embeddings are pivotal for generating synthetic speech through advanced neural network architectures like variational autoencoders or Generative Adversarial Networks (GANs). This process synthesizes new speech samples that retain the linguistic properties of the original data while varying in vocal intonations and environmental sounds, thereby enriching the training dataset with realistic, diverse samples. The integration of LLMs in this process, as explored by Xu ([207]) and Wu et al. ([159]), enables the generation of high-quality synthetic speech that significantly enhances training data diversity and model performance.

The final step is refinement, filteringa nd integration into DL training set which involve the refinement and filtering of the generated synthetic speech to ensure it meets quality standards without unwanted noise or artifacts. This step is critical to maintaining the usability of the synthetic samples in training robust speech recognition systems. Once refined, these samples are integrated into the main training dataset, where they contribute to a comprehensive and varied training environment. This enriched dataset is then used to train and continually refine deep learning models, ensuring they are well-adapted to a variety of speech patterns and acoustic environments. The effectiveness of this comprehensive training approach is supported by the work of Xu ([207]) and Ghosh et al. ([208]), who have demonstrated how diversified training sets can significantly enhance the generalizability and accuracy of speech recognition systems.

Table 3 shows the detailed survey of audio data augmentation performed using multimodal LLMs in the last 5 (2020 till) years:

4.3.2 Methods and Techniques.

• Background Noise Addition: Background noise addition is a prevalent method in speech data augmentation aimed at enhancing the robustness of speech recognition systems under varied acoustic environments. By introducing different types of ambient noises, such as traffic, crowd, or white noise, during the training phase, models learn to maintain accuracy despite auditory distractions. This method has been pivotal in scenarios where speech recognition must perform reliably in non-ideal and noisy conditions. For instance, the works by [207]

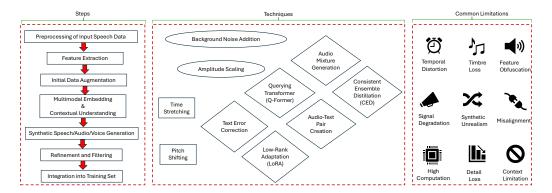


Fig. 7. LLM based speech data augmentation: showing the technical aspect of how audio/speech augmentation using LLM is performed, the techniques of augmenting speech data using LLM and their limitations

and [159] demonstrate how integrating complex audio backgrounds can prepare systems for real-world applications, significantly enhancing the environmental adaptability of speech recognition models. Additionally, [205] illustrates the effectiveness of this approach in the context of speech de-identification, where noise can mask personally identifiable information, enhancing privacy. [203] also utilizes background noise to challenge the robustness of audiovisual deepfake detection models, ensuring they can perform under diverse conditions.

- Amplititude Scaling: Amplitude scaling involves adjusting the volume levels of speech recordings to simulate various speaking and listening conditions. This technique is essential for training models to recognize speech across a spectrum of vocal intensities and distances from the sound source, from whispers to shouts. Amplitude scaling helps in normalizing the loudness of audio inputs, which is crucial for consistent model performance. [206] applies this method to enhance the emotion recognition capabilities of systems by training them to detect subtle variations in speech dynamics that may indicate emotional states. Similarly, [159] and [207] have demonstrated how varying amplitude can prepare models for real-life scenarios where audio levels are not constant. [208] uses amplitude scaling to test the resilience of audio classification systems, ensuring they remain effective regardless of volume variations.
- Time Stretching: Time stretching modifies the speed of speech playback without altering the pitch, effectively simulating different speech rates. This augmentation is crucial for developing ASR systems that can accurately transcribe inputs from speakers who articulate at varying speeds. By expanding or compressing the temporal duration of audio samples, models are trained to handle slow and fast speech effectively. Studies such as those by [206] and [204] have utilized time stretching to adapt models for emotional and secure speech recognition tasks, where delivery speed can vary significantly based on the speaker's emotional state or privacy concerns. Furthermore, [207] and [203] incorporate time stretching to enhance the adaptability of models in multimedia environments where speech tempo can change contextually.
- **Pitch Shifting**: Pitch shifting adjusts the pitch or tone of the speech while keeping the speed constant. This method is instrumental in training models to recognize voices across different age groups, genders, and vocal characteristics. By simulating a wide range of vocal pitches, speech recognition systems can better identify and understand speakers from diverse demographic backgrounds. [159] and [207] employ pitch shifting to diversify the acoustic properties of training datasets, improving the system's ability to generalize across different

Table 3. Survey of Multi-modal LLMs in Audio/Voice/Speech Data Augmentation (Peer Reviewed Papers, 2020-present)

LLM Name	Domain	Audio Augmentation Method	Key Insights
Instructor LLM & ChatGPT [159]	Audio Captioning	Fine-grained audio feature extraction and caption mix-ups	Achieved new SPIDEr-FL score record; won the 2023 DCASE AAC challenge. Mix-ups risk overfitting due to data com- plexity.
LLM-Assisted [207]	Audio-Text Pairing	Text embeddings and signal processing for audio-caption datasets	Improved performance on benchmarks; addressed lack of modifiers in datasets. Relies on alignment quality of text with audio.
LLM-Assisted [205]	Speech De- identification	Automated augmentation for robust PII detection	Enhanced accuracy for speech de- identification; reliant on LLM-generated data quality.
AV-Deepfake1M [203]	Deepfake Detection	LLM-driven audio-visual manipulations	Generated 1M+ videos; tested state-of- the-art methods for deepfake detection. Performance challenges persist.
ER-PTM-LLM-TTS [206]	Speech Emotion Recognition	Emotional TTS, Speech PTM, Text LLM integration	Boosted SER performance with cutting- edge methods (data2vec, GPT-4, Azure TTS); integration complexity is high.
Speech De-Id NER [204]	Named Entity Recognition (NER)	Synthetic speech-style text generation for semi-automatic PII annotation	Enhanced speech de-identification NER; semi-automatic process requires manual review.
ArzEn-LLM [209]	Code-Switched ASR	LLM integration for Egyptian Arabic-English ASR and MT systems	Improved code-switching translation and ASR handling; dependent on high- quality data integration.
Nor-BERT [210]	Hate Speech Detection	Lexical and semantic augmentations with Barlow Twins	Enhanced hate speech detection in Norwegian; reliant on dataset quality and scale.
AR-GPT-4 [211]	Emergency Response	AR-LLM integration for task efficiency	Improved situational awareness and task performance; dependent on real-time integration.
LLM-Commentator [212]	Sports Commentary	LLM for real-time football commentary generation	Generated accurate football commentary in real-time; requires high-quality domain-specific training.
LLM-HRC [213]	Human-Robot Collaboration	LLM for natural language programming in manufacturing	Improved HRC efficiency with intuitive interface; requires integration with Digital Twins and real-time control.
LAMB [214]	Education	LLM for AI-powered educational assistants	Streamlined AI integration into LMS; fo- cused on privacy and customizability. De- pendent on robust LMS integration and educational standards.
LaMini-Flan-T5 [215]	Video Summariza- tion	Abstractive summarization for YouTube videos	Provided concise summaries to improve accessibility; relies on accurate video transcripts.
ReSLM [216]	Spoken Dialog Systems	Retrieval-augmented dialog state tracking	Improved accuracy in domain-specific entity recognition; dependent on retrieval component quality.
MMed-Llama 3 [217]	Multilingual Health- care	Multilingual medical corpus for domain- specific adaptation	Facilitated multilingual medical under- standing with benchmarks; corpus diver- sity is critical for performance.
GRBAS-Net [218]	Voice Classification	Noise-resilient classification for pathological voices	Enhanced GRBAS scale classification; performance deteriorates with increased noise.

speakers. [208] and [206] also highlight the use of pitch variation to train more resilient and inclusive speech recognition and emotion detection models, ensuring effectiveness across varied vocal registers.

• **Text Error Correction**: Text error correction in the context of speech data augmentation often involves using LLMs to identify and correct transcription errors that arise from

speech-to-text processes. This technique enhances the accuracy of ASR (Automatic Speech Recognition) systems by refining the textual output using contextual understanding and language models. The LLMs, such as those mentioned in [204] and [208], are trained on vast datasets, allowing them to predict and replace erroneous words or phrases accurately. Furthermore, the integration of these models in systems like the one described by [207] helps in adjusting text outputs to better match the spoken input, significantly reducing the error rates in transcription. [219] also highlights the application of LLMs in enhancing comprehension and response accuracy by correcting semantic errors, thus improving the overall reliability of speech-driven applications.

- Querying Transformer (Q-former): The Querying Transformer, or Q-former, is an advanced model architecture that incorporates querying mechanisms into transformers for better handling and understanding of speech queries. This method is particularly useful in speech recognition systems where the context and intent behind spoken words are critical for accurate interpretation. By embedding querying capabilities, such as those discussed in [206] and [187], Q-formers can dynamically adjust their processing strategies based on the query's complexity and specificity. This adaptability is crucial in applications like customer service bots and interactive AI, where [213] and [220] have demonstrated significant improvements in user interaction and satisfaction by employing Q-formers to accurately address user inquiries.
- Audio Mixture Generation: Audio Mixture Generation involves creating composite audio tracks from multiple sources, which is pivotal in training robust ASR systems to handle overlapping speech and background noise. This technique uses LLMs to intelligently blend different audio signals, maintaining a balance that mimics real-world scenarios. Studies such as [207] and [208] utilize this method to generate training data that helps models learn to isolate relevant speech from noise. Additionally, [221] and [222] explore the effectiveness of audio mixture generation in enhancing the diversity and complexity of audio datasets, thus preparing ASR systems for more challenging acoustic environments.
- Low-Rank Adaptation (LoRA): LoRA is a technique used to fine-tune large LLMs efficiently by modifying only a small subset of model parameters, thus reducing computational costs while maintaining performance. In speech augmentation, LoRA can be applied to adapt pre-trained LLMs to specific audio tasks without extensive retraining. For instance, [206] and [204] apply LoRA to adjust models for emotional recognition and PII masking, respectively, by focusing on layers directly involved in these tasks. This method ensures that the LLMs remain lightweight and agile, as supported by [187] and [223], which highlight the practicality of LoRA in deploying advanced speech technologies in resource-constrained environments.
- Audio-Text Pair Creation: Audio-Text Pair Creation is central to training multimodal LLMs, where synchronization between spoken audio and corresponding textual data is crucial. This process involves generating or curating matched pairs of text and audio to train models in tasks like audio captioning and speech recognition. The effectiveness of this method is evident in works like [207] and [220], where aligned audio-text pairs improve the model's ability to learn contextual nuances. Additionally, [208] and [212] utilize this technique to enhance the accuracy and contextual relevance of generated captions, providing a richer training dataset that mimics real-world interactions.
- Consistent Ensemble Distillation (CED): CED) is a method that leverages the strengths
 of multiple models to create a single, more robust model. In the context of speech data
 augmentation, CED can be used to combine the outputs of various LLMs to enhance speech
 recognition accuracy under diverse conditions. This approach, as discussed in [206] and [204],
 involves distilling knowledge from multiple specialized models into a unified system that

exhibits improved performance and resilience. [213] and [220] further illustrate how CED facilitates the integration of diverse linguistic and acoustic features, enhancing the system's ability to handle complex speech patterns and ambient sounds effectively.

4.3.3 Limitations and Potential Solutions.

- Temporal Distortion: Temporal distortion is a significant limitation in LLM-based audio data augmentation due to the constraints of large language models (LLMs) in handling the temporal dynamics of speech [224, 225]. LLMs, primarily developed for processing text, lack the specialized architecture required to effectively manage time-dependent elements in audio signals [206]. This deficiency leads to challenges in maintaining the naturalness and rhythm of speech when the speed is altered through temporal distortion. Such modifications can make the speech sound unnatural or robotic, potentially degrading the training quality of speech recognition systems. Moreover, the alteration of speech speed can disrupt the acoustic cues essential for models to learn effectively, impacting their ability to perform accurately in real-world scenarios where speech tempo varies [205, 226]. Additionally, the modified timing can complicate the comprehension of speech by language models, as the distorted temporal features may hinder their ability to interpret syntactic and semantic information correctly. To address the temporal distortion in LLM-based audio augmentation effectively, future advancements should involve refining LLM architectures to accommodate audio-specific temporal dynamics, potentially through the integration of temporal attention mechanisms or recurrent neural network layers [19]. Additionally, developing hybrid models that merge LLMs with digital signal processing techniques could enhance the handling of variable speech rates, thereby preserving the naturalness of speech [227]. Furthermore, diversifying training datasets to include audio samples with varied speech tempos can improve model robustness, ensuring better performance across different real-world speech scenarios [19, 228].
- Timbre Loss: Timbre loss represents another significant technical challenge in LLM-based audio augmentation, primarily because LLM architectures, traditionally optimized for text, do not effectively preserve the complex spectral qualities that define an audio signal's unique timbre [206, 229]. This limitation is critical because timbre imparts the distinct character to voices or musical sounds, which is essential for applications like speech synthesis and music generation [230]. The alteration of timbre during processes such as pitch shifting or speed modification can result in audio outputs that fail to replicate the original sound's perceptual attributes, thereby diminishing the authenticity and effectiveness of the augmented audio in practical applications [231].

To address timbre loss in LLM-based audio augmentation, several approaches have been proposed such as Joint modeling of timbre and content [232], where the system employs a joint modeling approach that integrates timbre features with both supervised and self-supervised content representations. This enhances speaker similarity and intelligibility, allowing for more accurate reproduction detailed speaker characteristics. Likewise, Conditional flow matching-based decoder can optimize the alignment between timbre and content features. This leads to more natural and accurate voice conversions, preserving timbre qualities [232]. Additionally, semantic-acoustic integration approach integrates both semantic and acoustic features into a unified tokenization framework. By employing a distinctive "X-shaped" structure with two inputs and two outputs, it enables simultaneous embedding learning of semantic richness and acoustic fidelity for every token. This design helps in preserving timbre information alongside semantic content [233]. To further address timbre loss in LLM-based audio augmentation, additional strategies could include the implementation of advanced deep learning architectures such as GANs are tailored specifically for audio

tasks. These networks can learn to generate highly realistic audio samples by training on a competitive dynamic between the generative model producing audio and the discriminative model evaluating it [32, 234]. Additionally, integrating multimodal data during the training phase can enhance the model's ability to understand and replicate timbre by exposing it to a broader range of audio characteristics [235]. Techniques like transfer learning could also be employed, where models pre-trained on vast, diverse datasets are fine-tuned with specific timbre data, improving the model's generalization capabilities to new voices or sounds while maintaining the unique timbral qualities [236].

• Feature Obfuscation: Feature obfuscation is a limitation of LLM-based speech augmentation due to the challenges it presents in preserving important speech characteristics while attempting to protect privacy or modify content. This limitation manifests in several ways such as Loss of acoustic fidelity [204] and difficulty in preserving prosody [237]. When obfuscating features for privacy reasons, such as in speech de-identification, there's a risk of degrading the overall acoustic quality of the augmented speech [204]. This can impact the naturalness and intelligibility of the output. LLMs may struggle to maintain the original prosodic features of speech when augmenting or obfuscating content, potentially leading to unnatural-sounding output [237]. Additionally, feature obfuscation inadvertently risks obscuring critical acoustic features. For example, methods aiming to anonymize speaker identity might modify pitch or tone, potentially leading to a loss in the naturalness and expressiveness of speech [238]. This degradation not only affects the audio's perceptual quality but can also impair the effectiveness of speech recognition systems that rely on distinct acoustic signals for accurate processing. Furthermore, when LLMs attempt to balance feature obfuscation with maintaining intelligibility, the resulting speech might not faithfully represent the original speaker's emotional or prosodic cues, thus diminishing the listener's experience and the speech's emotional conveyance.

Addressing feature obfuscation in LLM-based speech augmentation requires a balanced approach that preserves essential speech characteristics while maintaining privacy. One effective method is the implementation of differential privacy techniques during the training phase of speech synthesis models [238]. This involves adding controlled noise to training data, which helps obscure individual speech features without significantly degrading overall audio quality. Additionally, advanced machine learning strategies like adversarial training can be employed, where models are trained to resist attempts at extracting specific features, thereby enhancing privacy [239, 240].

• Signal Degradation: Signal degradation represents a substantial challenge and limitation in LLM-based audio or speech augmentation due to its adverse effects on the audio quality and perceptual integrity of the output. In augmentation processes that involve LLMs, signal degradation typically arises from operations such as compression, format conversion, or even the introduction of synthetic elements that can diminish the audio's natural qualities [241, 242]. This degradation can crucially impair the audio's clarity and fidelity, making it less suitable for applications reliant on high-quality audio inputs, such as speech recognition technologies and auditory user interfaces [227]. Furthermore, the authenticity and expressiveness of speech are often compromised, leading to outputs that might not accurately convey the intended emotions [226].

To address the issue of signal degradation in LLM-based speech augmentation, it's essential to integrate advanced audio processing techniques that enhance signal integrity while maintaining or improving the natural characteristics of speech [19, 227]. One effective approach involves the use of sophisticated denoising algorithms that can remove unwanted noise

without affecting the core audio signal. Additionally, implementing dynamic range compression can help maintain audio quality by balancing the volume levels within a speech, thus preventing distortions caused by volume peaks or lows. Further advancements can be made by utilizing high-resolution signal processing techniques during the augmentation process to preserve the fine details of the speech waveform. Machine learning models, particularly those trained on a diverse set of high-quality audio samples, can be employed to learn and predict optimal signal characteristics that minimize loss during transformations.

• Synthetic Unrealism: Synthetic Unrealism poses a significant challenge in audio data augmentation using multimodal LLMs due to the potential introduction of unrealistic or inconsistent audio features [243]. This phenomenon can lead to the generation of augmented data that does not accurately represent real-world audio characteristics, potentially compromising the model's ability to generalize to authentic scenarios [244]. The issue is exacerbated by the complex nature of audio data, which encompasses various dimensions such as pitch, tempo, and timbre. LLMs, while adept at generating diverse content, may struggle to maintain the intricate relationships between these audio components, resulting in synthetic samples that lack coherence or natural acoustic properties [243, 245]. Furthermore, the risk of overfitting to artificially generated patterns increases, potentially leading to reduced model performance on genuine audio inputs.

To tackle the issue of synthetic unrealism in LLM-based audio data augmentation, a multifaceted approach focusing on enhancing the model's capability to generate more realistic and coherent audio samples is essential. First, integrating more comprehensive and high-fidelity training datasets can provide a richer foundation for learning authentic audio characteristics [246]. This can involve using recordings from diverse environments and contexts to cover a broader spectrum of real-world audio features. Secondly, applying advanced machine learning techniques such as conditional GANs (cGANs) could enforce more stringent checks on the realism of generated audio [31, 33]. These networks can learn to distinguish between real and synthetic audio samples, pushing the generative model to produce outputs that are indistinguishable from genuine recordings. Finally, regularizing the training process to prevent overfitting is crucial. Techniques like dropout, data augmentation (ironically), and cross-validation can be employed to ensure the LLM does not learn to replicate only the training data's patterns but can generalize well across unseen audio inputs [247].

• Misalignment: Misalignment in LLM-based audio or speech data augmentation refers to discrepancies between augmented audio data and the original audio's characteristics, such as emotional tone or linguistic details [248]. This issue typically arises because LLMs, originally designed for text processing, may not adequately capture complex audio features like pitch, timbre, or rhythm [248, 249]. Such misalignment is problematic for deep learning applications reliant on precise, high-quality audio data for training. For example, in speech recognition or voice-assisted AI, misaligned data can lead to systems that misinterpret user commands or fail in real applications, reducing the reliability and effectiveness of AI interactions with human speech [250].

To address misalignment in LLM-based audio augmentation for deep learning applications, future solutions should focus on enhancing model sensitivity. One effective approach is to integrate audio-specific adaptations into the LLM architectures, such as using convolutional layers that can better capture the temporal and spectral dynamics of sound [251]. Advanced techniques like attention mechanisms could also be employed to focus on critical features of the audio signal, improving the model's ability to retain important acoustic properties during augmentation [252, 253]. Moreover, incorporating multimodal training data that includes both audio and corresponding textual annotations can help improve the alignment between

the generated audio and its intended meaning [254]. This would enable the LLM to learn more comprehensive representations of audio features and their contextual significance. Additionally, continuous evaluation and feedback loops involving real-world testing and user input should be established to iteratively refine the models, ensuring that the audio outputs remain aligned with practical applications and user expectations.

• High Computation: LLM-based data augmentation for audio or speech is computationally intensive primarily due to the sheer size and complexity of these models. Large language models contain billions of parameters, demanding extensive memory and processing power for operations [97]. This computational requirement becomes a significant challenge because it necessitates the use of specialized hardware like GPUs or TPUs, which can be costly and less accessible for many researchers and developers [255]. Moreover, the energy-intensive nature of training and deploying these models adds to their operational costs and environmental impact [256, 257]. This high computational demand limits the scalability of deploying LLMs for audio data augmentation, especially in environments with limited hardware resources. Additionally, the requirement for significant computational resources can impede rapid testing and iteration of models, slowing down the development cycle and innovation in audio processing applications.

To address the high computational demands of LLM-based audio augmentation, several efficiency-enhancing strategies can be implemented. Model pruning and quantization are key techniques that streamline the model by reducing parameters and computation precision, respectively, without significantly impacting performance [258]. Knowledge distillation transfers expertise from a large model to a smaller, more efficient one, maintaining accuracy while decreasing computational load [259]. Efficient hardware utilization, such as specialized neural network processors or hardware accelerators like FPGAs, can boost processing speed and reduce power consumption [260]. Likewise, Adaptive computing techniques adjust model complexity based on task requirements, conserving resources for simpler tasks [261].

- Detail Loss: Detail loss in LLM-based audio data augmentation significantly hampers the utility of this technology due to several inherent limitations associated with audio complexity [207]. Audio data consists of dynamic acoustic features such as pitch, tempo, timbre, and emotional inflections, which are crucial for maintaining the authenticity of the sound [262]. LLMs, although capable of generating varied audio content, often struggle with preserving these intricate details. This limitation arises partly because of the inadequate representation of fine-grained features in the training datasets, which tend not to include high-quality textaudio pairs that capture detailed acoustic properties and object relationships. For instance, in speech augmentation, LLM might modify a voice's fundamental frequency but fail to retain the speaker's distinct vocal characteristics or the subtleties of their emotional tone [226]. Similarly, in music augmentation, critical attributes like the attack and decay phases of notes played by different instruments might be inaccurately rendered or completely lost [263]. Such detail loss not only diminishes the fidelity of the augmented audio compared to real-world sounds but also limits the practical applications of LLMs in fields requiring high precision in audio reproduction, such as virtual reality, filmmaking, and advanced user interfaces.
 - To reduce detail loss in LLM-based audio augmentation, enhancing training datasets with high-quality, diverse recordings and employing specialized neural network architectures and multi-modal learning approaches can significantly improve the model's ability to accurately generate complex audio data.
- Context Limitation: Context limitation in LLM-based speech augmentation refers to the challenge these models face in accurately understanding and generating contextually appropriate audio responses [264]. Unlike simple text generation, speech involves complex

elements such as tone, inflection, and rhythm, which are deeply embedded in the specific contexts of conversation or narration [265]. Scientifically, the main issue arises because LLMs typically generate outputs based on patterns recognized in training data, without a genuine understanding of human emotions, intentions, or the subtleties of spoken language dynamics [266]. This becomes a significant limitation in applications where speech needs to convey more than just words, such as in emotional speech synthesis for virtual assistants, interactive learning environments, or customer service bots. The inability to incorporate real-time context and emotional undertones often results in responses that, while grammatically correct, can seem out of place, emotionally flat, or inappropriate to human listeners.

To overcome context limitation in LLM-based speech data augmentation, future strategies should aim to enhance models' contextual and emotional understanding through advanced training methodologies and architectural improvements. Implementing context-aware training, where models are exposed to a diverse range of speech scenarios with varying emotional and situational contexts, can enrich their understanding. For example, training on datasets from theatrical dialogues or emotionally charged speeches could help models better recognize and replicate context-specific speech patterns. Additionally, integrating Emotional Neural Networks (EmoNNs), which are specially trained to recognize and replicate human emotions in speech, can significantly enhance the emotional intelligence of LLMs. Multi-modal learning is another promising approach, where combining inputs like text, audio cues, and visual data such as facial expressions or gestures can deepen models' contextual comprehension. For instance, training a model using both the audio and video of a speaker can teach it to correlate speech patterns with corresponding physical expressions. Furthermore, developing adaptive models that adjust their outputs based on real-time feedback can also help. Interactive voice response systems that modify their tone in response to user emotions like frustration or happiness exemplify this approach.

5 Discussion

This survey provides an exhaustive review of the latest advancements in LLM-based data augmentation, covering a broad range of applications across image, text, and audio data modalities. It includes both 2D and 3D image data augmentation techniques, ensuring a holistic understanding of the field. The survey delves into the technical processes, methods, and techniques of LLM-based data augmentation, offering detailed insights that are crucial for researchers and practitioners. This depth extends to a critical examination of the limitations and potential solutions, enhancing the practical value of the survey. By focusing on publications from the last five years, the survey ensures that the findings are relevant and up-to-date, reflecting the cutting-edge developments in LLM applications and data augmentation strategies.

5.1 Impact

Theoretical Impact This survey contributes significantly to the theoretical understanding of LLM-based data augmentation by identifying methodologies that enhance the robustness and generalization of AI models. These insights are essential for enabling reliable and adaptive performance in diverse real-world scenarios. By critically evaluating current limitations and gaps in the literature, the survey not only enriches the foundational knowledge of the field but also provides a roadmap for addressing these challenges. Additionally, the proposed research directions stimulate further innovation, guiding researchers toward developing advanced, more effective AI systems.

Practical Impact The practical implications of this survey are far-reaching for both academia and industry. For practitioners, it offers a detailed analysis of state-of-the-art techniques that can be directly applied to improve model performance across various applications, including computer

vision, natural language processing, and audio processing. The survey also identifies actionable solutions to common challenges, equipping developers and engineers with tools to implement efficient and scalable data augmentation pipelines. Stakeholders can use this knowledge to harness the potential of LLM-based data augmentation for innovation in their respective domains.

5.2 Future Perspectives

The future of LLM-based data augmentation spans a diverse range of innovations, as illustrated in Figure 8. Here, image augmentation techniques are projected to emphasize 3D context and multi-view data processing, supporting more realistic scene representations and advanced real-time editing pipelines. At the same time, enhanced domain specialization will drive the adaptation of augmentation strategies to particular fields such as healthcare, manufacturing, or robotics, all while maintaining semantic consistency through robust validation mechanisms. Similarly, text augmentation is set to benefit from fact-based, knowledge-grounded generation, improving the reliability and interpretability of synthetic text. This is especially pertinent in multilingual low-resource contexts, where LLMs could fill data gaps for underrepresented languages, all the while supporting fine-grained style and emotion control to produce more expressive outputs and on-the-fly language adaptation in real-world communication systems.

In the realm of speech augmentation, emotion and prosody preservation will be key to delivering authentic, human-like audio data, making voice-based AI more natural and empathetic. High-fidelity timbre retention likewise remains an open challenge, especially for sensitive applications such as assistive speech devices and high-end multimedia production. Augmentation tailored to context-aware accent integration promises a more inclusive approach, broadening AI's reach across diverse linguistic communities. Finally, robust streaming augmentation methods could enable real-time transformations of audio for live scenarios, such as simultaneous interpretation or interactive voice assistants.

Additionally, the advent of reinforcement learning-based methodologies such as DeepSeek R1 heralds a transformative shift in LLM based data augmentation [267]. Traditionally, LLMs have been dependent on large, meticulously annotated datasets, which can restrict their adaptability and scope for innovation. However, DeepSeek R1 shifts away from this reliance by using reinforcement learning (RL) to enable models to continuously learn and evolve autonomously by interacting with their environment and adjusting based on feedback. This shift is particularly transformative for data augmentation strategies. Reinforcement learning allows models like DeepSeek R1 to not only generate their own data but also to continuously refine this data in response to new challenges and feedback. This dynamic approach to data generation represents a significant move away from static, pre-labeled datasets, reducing costs and dependency on human annotation. The implications for data augmentation are profound. As models become capable of self-augmentation, they can explore a broader range of scenarios and adapt to complex, unforeseen challenges more effectively than models restricted by their initial training data. This not only enhances the flexibility and depth of the models' knowledge but also opens up new possibilities for efficiency in model training. As reinforcement learning continues to advance, it is set to reshape the landscape of data augmentation, promising a future where AI systems are more robust, context-aware, and adaptable. This development indicates a new era where LLMs can surpass traditional capabilities, driven by their ability to learn independently and innovate beyond the boundaries of their initial programming.

6 Conclusion

In this comprehensive survey, we have explored the role of multimodal LLMs within the domain of AI for data augmentation practice. We focusing specifically on three fundamental data modalities:

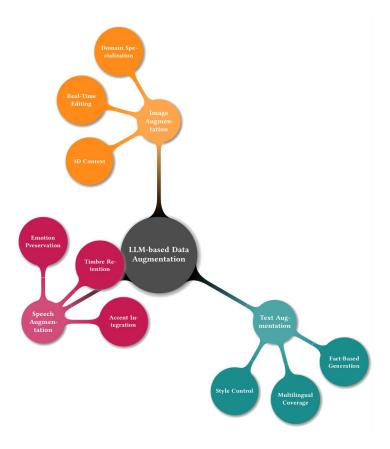


Fig. 8. A mind map illustrating future perspectives of LLM-based data augmentation for image, text, and speech domains.

image, text, and speech. The findings of this survey shows that over the past five years (2020 onwards), there has been a significant increase in the publication of peer-reviewed and preprint papers that utilize LLMs for data augmentation. Our survey methodically assessed the state-of-theart techniques reported in recent literature, extracting key details about the technical processes employed in LLM-based data augmentation. We delved into the diverse methods and techniques utilized to augment data through LLMs, providing a clear overview of how these models are applied to enhance the quality and effectiveness of datasets across different applications. This included a thorough analysis of augmentation strategies for 2D and 3D images, the enhancement of textual data for better language model training, and the augmentation of audio data to improve the robustness and accuracy of speech recognition systems. Moreover, our study identified limitations inherent in current LLM-based data augmentation strategies. These issues range from the potential for introducing bias and reducing model generalizability to challenges in maintaining the semantic integrity and contextual relevance of augmented data. To address these limitations, we discussed potential solutions that could pave the way for more effective and reliable data augmentation practices in the future. The findings of this survey can be used to throry for next generation data augmentation.

Ranjan Sapkota led research conceptualization, methodology, and writing; Shaina Raza, Maged Shoman, and Achyut Paudel contributed to review and methodology; Manoj Karkee provided overall supervision and funding.

References

- [1] Guillermo Iglesias, Edgar Talavera, Ángel González-Prieto, Alberto Mozo, and Sandra Gómez-Canaval. Data augmentation techniques in time series domain: a survey and taxonomy. *Neural Computing and Applications*, 35(14): 10123–10145, 2023.
- [2] Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. *Journal of big data*, 6(1):1–48, 2019.
- [3] Alexander J Ratner, Henry Ehrenberg, Zeshan Hussain, Jared Dunnmon, and Christopher Ré. Learning to compose domain-specific transformations for data augmentation. Advances in neural information processing systems, 30, 2017.
- [4] Alhassan Mumuni and Fuseini Mumuni. Data augmentation: A comprehensive survey of modern approaches. Array, 16:100258, 2022.
- [5] Brian Kenji Iwana and Seiichi Uchida. An empirical survey of data augmentation for time series classification with neural networks. Plos one, 16(7):e0254841, 2021.
- [6] Kiran Maharana, Surajit Mondal, and Bhushankumar Nemade. A review: Data pre-processing and data augmentation techniques. Global Transitions Proceedings, 3(1):91–99, 2022.
- [7] Markus Bayer, Marc-André Kaufhold, Björn Buchhold, Marcel Keller, Jörg Dallmeyer, and Christian Reuter. Data augmentation in natural language processing: a novel text generation approach for long and short text classifiers. International journal of machine learning and cybernetics, 14(1):135–150, 2023.
- [8] Parvinder Kaur, Baljit Singh Khehra, and Er Bhupinder Singh Mavi. Data augmentation for object detection: A review. In 2021 IEEE International Midwest Symposium on Circuits and Systems (MWSCAS), pages 537–543. IEEE, 2021.
- [9] Hugo Queiroz Abonizio, Emerson Cabrera Paraiso, and Sylvio Barbon. Toward text data augmentation for sentiment analysis. *IEEE Transactions on Artificial Intelligence*, 3(5):657–668, 2021.
- [10] Ayesha Pervaiz, Fawad Hussain, Huma Israr, Muhammad Ali Tahir, Fawad Riasat Raja, Naveed Khan Baloch, Farruh Ishmanov, and Yousaf Bin Zikria. Incorporating noise robustness in speech command recognition by noise augmentation of training data. Sensors, 20(8):2326, 2020.
- [11] Bandhav Veluri, Malek Itani, Tuochao Chen, Takuya Yoshioka, and Shyamnath Gollakota. Look once to hear: Target speech hearing with noisy examples. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pages 1–16, 2024.
- [12] Yuxiao Zhang, Alexander Carballo, Hanting Yang, and Kazuya Takeda. Perception and sensing for autonomous vehicles under adverse weather conditions: A survey. ISPRS Journal of Photogrammetry and Remote Sensing, 196: 146–177, 2023.
- [13] Lisa Jöckel, Michael Kläs, and Silverio Martínez-Fernández. Safe traffic sign recognition through data augmentation for autonomous vehicles software. In 2019 IEEE 19th International Conference on Software Quality, Reliability and Security Companion (QRS-C), pages 540–541. IEEE, 2019.
- [14] Hoo-Chang Shin, Neil A Tenenholtz, Jameson K Rogers, Christopher G Schwarz, Matthew L Senjem, Jeffrey L Gunter, Katherine P Andriole, and Mark Michalski. Medical image synthesis for data augmentation and anonymization using generative adversarial networks. In Simulation and Synthesis in Medical Imaging: Third International Workshop, SASHIMI 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Proceedings 3, pages 1–11. Springer, 2018.
- [15] Phillip Chlap, Hang Min, Nym Vandenberg, Jason Dowling, Lois Holloway, and Annette Haworth. A review of medical image data augmentation techniques for deep learning applications. *Journal of Medical Imaging and Radiation Oncology*, 65(5):545–563, 2021.
- [16] Gözde Gül Şahin. To augment or not to augment? a comparative study on text augmentation techniques for low-resource nlp. *Computational Linguistics*, 48(1):5–42, 2022.
- [17] Jiaao Chen, Derek Tam, Colin Raffel, Mohit Bansal, and Diyi Yang. An empirical survey of data augmentation for limited data learning in nlp. *Transactions of the Association for Computational Linguistics*, 11:191–211, 2023.
- [18] Xiang Wang, Kai Wang, and Shiguo Lian. A survey on face data augmentation for the training of deep neural networks. *Neural computing and applications*, 32(19):15503–15531, 2020.
- [19] Bosheng Ding, Chengwei Qin, Ruochen Zhao, Tianze Luo, Xinze Li, Guizhen Chen, Wenhan Xia, Junjie Hu, Luu Anh Tuan, and Shafiq Joty. Data augmentation using llms: Data perspectives, learning paradigms and challenges. In Findings of the Association for Computational Linguistics ACL 2024, pages 1679–1705, 2024.
- [20] Fahim Sufi. Generative pre-trained transformer (gpt) in research: A systematic review on data augmentation. Information, 15(2):99, 2024.

- [21] Linmei Hu, Zeyi Liu, Ziwang Zhao, Lei Hou, Liqiang Nie, and Juanzi Li. A survey of knowledge enhanced pre-trained language models. *IEEE Transactions on Knowledge and Data Engineering*, 2023.
- [22] Ander Gracia Moisés, Ignacio Vitoria Pascual, José Javier Imas González, and Carlos Ruiz Zamarreño. Data augmentation techniques for machine learning applied to optical spectroscopy datasets in agrifood applications: A comprehensive review. Sensors, 23(20):8562, 2023.
- [23] Dimah Al-Fraihat, Yousef Sharrab, Faisal Alzyoud, Ayman Qahmash, Monther Tarawneh, and Adi Maaita. Speech recognition utilizing deep learning: A systematic review of the latest developments. *Human-centric Computing and Information Sciences*, 14, 2024.
- [24] Olusola O Abayomi-Alli, Robertas Damaševičius, Atika Qazi, Mariam Adedoyin-Olowe, and Sanjay Misra. Data augmentation and deep learning methods in sound classification: A systematic review. Electronics, 11(22):3795, 2022.
- [25] Pei Liu, Xuemin Wang, Chao Xiang, and Weiye Meng. A survey of text data augmentation. In 2020 International Conference on Computer Communication and Network Security (CCNS), pages 191–195. IEEE, 2020.
- [26] Nino Cauli and Diego Reforgiato Recupero. Survey on videos data augmentation for deep learning models. Future Internet, 14(3):93, 2022.
- [27] Markus Bayer, Marc-André Kaufhold, and Christian Reuter. A survey on data augmentation for text classification. ACM Computing Surveys, 55(7):1–39, 2022.
- [28] Teerath Kumar, Rob Brennan, Alessandra Mileo, and Malika Bendechache. Image data augmentation approaches: A comprehensive survey and future directions. IEEE Access, 2024.
- [29] Salma Fayaz, Syed Zubair Ahmad Shah, Nusrat Mohi ud din, Naillah Gul, and Assif Assad. Advancements in data augmentation and transfer learning: A comprehensive survey to address data scarcity challenges. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 17(8):14–35, 2024.
- [30] Alhassan Mumuni, Fuseini Mumuni, and Nana Kobina Gerrar. A survey of synthetic data augmentation methods in machine vision. Machine Intelligence Research, pages 1–39, 2024.
- [31] Peiyao Sheng, Zhuolin Yang, Hu Hu, Tian Tan, and Yanmin Qian. Data augmentation using conditional generative adversarial networks for robust speech recognition. In 2018 11th international symposium on Chinese spoken language processing (ISCSLP), pages 121–125. IEEE, 2018.
- [32] Yanmin Qian, Hu Hu, and Tian Tan. Data augmentation using generative adversarial networks for robust speech recognition. *Speech Communication*, 114:1–9, 2019.
- [33] Aamir Wali, Zareen Alamgir, Saira Karim, Ather Fawaz, Mubariz Barkat Ali, Muhammad Adan, and Malik Mujtaba. Generative adversarial networks for speech processing: A review. Computer Speech & Language, 72:101308, 2022.
- [34] Angela Carrera-Rivera, William Ochoa, Felix Larrinaga, and Ganix Lasa. How-to conduct a systematic literature review: A quick guide for computer science research. *MethodsX*, 9:101895, 2022.
- [35] National Institutes of Health. Guiding principles for ethical research, n.d. URL https://www.nih.gov/health-information/nih-clinical-research-trials-you/guiding-principles-ethical-research. Accessed: 2025-01-25.
- [36] Gopal Datt Joshi and Jayanthi Sivaswamy. Colour retinal image enhancement based on domain knowledge. In 2008 Sixth Indian Conference on Computer Vision, Graphics & Image Processing, pages 591–598. IEEE, 2008.
- [37] J-L Starck, Fionn Murtagh, Emmanuel J Candès, and David L Donoho. Gray and color image contrast enhancement by the curvelet transform. *IEEE Transactions on image processing*, 12(6):706–717, 2003.
- [38] Werner Frei. Image enhancement by histogram hyperbolization. *Computer Graphics and Image Processing*, 6(3): 286–294, 1977.
- [39] Jong-Sen Lee. Digital image enhancement and noise filtering by use of local statistics. *IEEE transactions on pattern analysis and machine intelligence*, (2):165–168, 1980.
- [40] David J Ketcham. Real-time image enhancement techniques. In *Image processing*, volume 74, pages 120–125. SPIE, 1976.
- [41] Stanley Osher and Leonid I Rudin. Feature-oriented image enhancement using shock filters. SIAM Journal on numerical analysis, 27(4):919–940, 1990.
- [42] Sankar K Pal and Robert A King. Image enhancement using fuzzy set. Electronics letters, 16(10):376-378, 1980.
- [43] Sung Cheol Park, Min Kyu Park, and Moon Gi Kang. Super-resolution image reconstruction: a technical overview. *IEEE signal processing magazine*, 20(3):21–36, 2003.
- [44] Simon Gibson, Jonathan Cook, Toby Howard, Roger Hubbold, and Daniel Oram. Accurate camera calibration for off-line, video-based augmented reality. In *Proceedings. International Symposium on Mixed and Augmented Reality*, pages 37–46. IEEE, 2002.
- [45] Manik Varma and Andrew Zisserman. A statistical approach to material classification using image patch exemplars. *IEEE transactions on pattern analysis and machine intelligence*, 31(11):2032–2047, 2008.
- [46] Monica Rubio, Arturo Quintana, Hebert Pérez-Rosés, Ricardo Quirós, and Emilio Camahort. Jittering reduction in marker-based augmented reality systems. In Computational Science and Its Applications-ICCSA 2006: International Conference, Glasgow, UK, May 8-11, 2006. Proceedings, Part I 6, pages 510–517. Springer, 2006.

[47] Sabzali Aghagolzadeh and Okan K Ersoy. Transform image enhancement. Optical Engineering, 31(3):614-626, 1992.

- [48] Miroslav Goljan and Jessica Fridrich. Camera identification from cropped and scaled images. In Security, Forensics, Steganography, and Watermarking of Multimedia Contents X, volume 6819, pages 154–166. SPIE, 2008.
- [49] Hayit Greenspan, Charles H Anderson, and Sofia Akber. Image enhancement by nonlinear extrapolation in frequency space. IEEE Transactions on Image Processing, 9(6):1035–1048, 2000.
- [50] Xiaojin Zhu, Andrew B Goldberg, Mohamed Eldawy, Charles R Dyer, and Bradley Strock. A text-to-picture synthesis system for augmenting communication. In AAAI, volume 7, pages 1590–1595, 2007.
- [51] Philip Glenny Edmonds. Semantic representations of near-synonyms for automatic lexical choice. University of Toronto, 1999
- [52] Kobus Barnard and Matthew Johnson. Word sense disambiguation with pictures. Artificial Intelligence, 167(1-2): 13–30, 2005.
- [53] Constantinos Boulis and Mari Ostendorf. Text classification by augmenting the bag-of-words representation with redundancy-compensated bigrams. In *Proc. of the International Workshop in Feature Selection in Data Mining*, pages 9–16. Citeseer, 2005.
- [54] E Ben-Naim and PL Krapivsky. Addition-deletion networks. Journal of Physics A: Mathematical and theoretical, 40 (30):8607, 2007.
- [55] Danielle S McNamara, Eileen Kintsch, Nancy Butler Songer, and Walter Kintsch. Are good texts always better? interactions of text coherence, background knowledge, and levels of understanding in learning from text. *Cognition and instruction*, 14(1):1–43, 1996.
- [56] Shinichi Nakagawa and Robert P Freckleton. Missing inaction: the dangers of ignoring missing data. *Trends in ecology & evolution*, 23(11):592–596, 2008.
- [57] Karen Kukich. Techniques for automatically correcting words in text. ACM computing surveys (CSUR), 24(4):377–439, 1992.
- [58] Susan W McRoy, Songsak Channarukul, and Syed S Ali. An augmented template-based approach to text realization. Natural Language Engineering, 9(4):381–420, 2003.
- [59] Ismail Haritaoglu. Scene text extraction and translation for handheld devices. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, volume 2, pages II–II. IEEE, 2001.
- [60] Hua Yan, William I Grosky, and Farshad Fotouhi. Augmenting the power of lsi in text retrieval: Singular value rescaling. Data & Knowledge Engineering, 65(1):108–125, 2008.
- [61] Martin Kay. The proper place of men and machines in language translation. machine translation, 12:3-23, 1997.
- [62] Wessel Kraaij, Jian-Yun Nie, and Michel Simard. Embedding web-based statistical translation models in cross-language information retrieval. Computational Linguistics, 29(3):381–419, 2003.
- [63] Pascale Fung and Kathleen McKeown. A technical word-and term-translation aid using noisy parallel corpora across language groups. *Machine translation*, 12:53–87, 1997.
- [64] Inderjit S Dhillon, Yuqiang Guan, and Jacob Kogan. Iterative clustering of high dimensional text data augmented by local search. In 2002 IEEE International Conference on Data Mining, 2002. Proceedings., pages 131–138. IEEE, 2002.
- [65] Michael Cohen, Shigeaki Aoki, and Nobuo Koizumi. Augmented audio reality: Telepresence/vr hybrid acoustic environments. In Proceedings of 1993 2nd IEEE International Workshop on Robot and Human Communication, pages 361–364. IEEE, 1993.
- [66] James H Brandenburg, Wayne Kirkham, and Danna Koschkee. Vocal cord augmentation with autogenous fat. The Laryngoscope, 102(5):495–500, 1992.
- [67] Kazuhisa Watanabe, S Murakami, HIROSHI Ishikawa, and TAKAHIKO Kamae. Audio and visually augmented teleconferencing. Proceedings of the IEEE, 73(4):656–670, 1985.
- [68] Chris Schmandt, Mark S. Ackerman, and Debby Hindus. Augmenting a window system with speech input. Computer, 23(8):50-56, 1990.
- [69] Scott G Adams and Anthony E Lang. Can the lombard effect be used to improve low voice intensity in parkinson's disease? European Journal of Disorders of Communication, 27(2):121–127, 1992.
- [70] Richard JM van Hoesel and Richard S Tyler. Speech perception, localization, and lateralization with bilateral cochlear implants. The Journal of the Acoustical Society of America, 113(3):1617–1630, 2003.
- [71] Jong Ho Won, Steven M Schimmel, Ward R Drennan, Pamela E Souza, Les Atlas, and Jay T Rubinstein. Improving performance in noise for hearing aids and cochlear implants using coherent modulation filtering. *Hearing research*, 239(1-2):1–11, 2008.
- [72] Yoshitaka Nishimura, Mitsuru Ishizuka, Kazuhiro Nakadai, Mikio Nakano, and Hiroshi Tsujino. Speech recognition for a humanoid with motor noise utilizing missing feature theory. In 2006 6th IEEE-RAS International Conference on Humanoid Robots, pages 26–33. IEEE, 2006.
- [73] Aki Härmä, Julia Jakka, Miikka Tikander, Matti Karjalainen, Tapio Lokki, Jarmo Hiipakka, and Gaëtan Lorho. Augmented reality audio for mobile and wearable appliances. Journal of the Audio Engineering Society, 52(6):618–639,

2004.

- [74] Wei Shu and Joseph S Chang. Power supply noise in analog audio class d amplifiers. IEEE Transactions on Circuits and Systems I: Regular Papers, 56(1):84–96, 2008.
- [75] Samir S Yadav and Shivajirao M Jadhav. Deep convolutional neural network based medical image classification for disease diagnosis. *Journal of Big data*, 6(1):1–18, 2019.
- [76] Fouzia Altaf, Syed MS Islam, Naveed Akhtar, and Naeem Khalid Janjua. Going deep in medical image analysis: concepts, methods, challenges, and future directions. *IEEE Access*, 7:99540–99572, 2019.
- [77] Manli Shu, Yu Shen, Ming C Lin, and Tom Goldstein. Adversarial differentiable data augmentation for autonomous systems. In 2021 IEEE International Conference on Robotics and Automation (ICRA), pages 14069–14075. IEEE, 2021.
- [78] Daobilige Su, He Kong, Yongliang Qiao, and Salah Sukkarieh. Data augmentation for deep learning based semantic segmentation and crop-weed classification in agricultural robotics. Computers and Electronics in Agriculture, 190: 106418, 2021.
- [79] Byeong-Cheol Jo, Tak-Sung Heo, Yeongjoon Park, Yongmin Yoo, Won Ik Cho, and Kyungsun Kim. Dagam: data augmentation with generation and modification. *arXiv preprint arXiv:2204.02633*, 2022.
- [80] Ranjan Sapkota and Manoj Karkee. Generative ai in agriculture: Creating image datasets using dall.e's advanced large language model capabilities. arXiv preprint arXiv:2307.08789, 2023.
- [81] Mikel Hernandez, Gorka Epelde, Ane Alberdi, Rodrigo Cilla, and Debbie Rankin. Synthetic data generation for tabular health records: A systematic review. Neurocomputing, 493:28–45, 2022.
- [82] Fabio Garcea, Alessio Serra, Fabrizio Lamberti, and Lia Morra. Data augmentation for medical imaging: A systematic literature review. *Computers in Biology and Medicine*, 152:106391, 2023.
- [83] Ranjan Sapkota, Rizwan Qureshi, Syed Zohaib Hassan, John Shutske, Maged Shoman, Muhammad Sajjad, Fayaz Ali Dharejo, Achyut Paudel, Jiajia Li, Zhichao Meng, et al. Multi-modal llms in agriculture: A comprehensive review. Authorea Preprints, 2024.
- [84] Jia Shijie, Wang Ping, Jia Peiyi, and Hu Siping. Research on data augmentation for image classification based on convolution neural networks. In 2017 Chinese automation congress (CAC), pages 4165–4170. IEEE, 2017.
- [85] Piyush Vyas, Kaushik Muthusamy Ragothaman, Akhilesh Chauhan, and Bhaskar Rimal. Data augmentation and generative machine learning on the cloud platform. *International Journal of Information Technology*, 16(8):4833–4843, 2024.
- [86] Shuai Wang, Yexin Yang, Zhanghao Wu, Yanmin Qian, and Kai Yu. Data augmentation using deep generative models for embedding based speaker recognition. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 28: 2598–2609, 2020.
- [87] Pascale Fung and Dekai Wu. Statistical augmentation of a chinese machine-readable dictionary. arXiv preprint cmp-lg/9406015, 1994.
- [88] Thomas G Dietterich, Hermann Hild, and Ghulum Bakiri. A comparison of id3 and backpropagation for english text-to-speech mapping. *Machine Learning*, 18:51–80, 1995.
- [89] Donald B Rubin. Comment: A noniterative sampling/importance resampling alternative to the data augmentation algorithm for creating a few imputations when fractions of missing information are modest: The sir algorithm. *Journal of the American Statistical Association*, 82(398):542–543, 1987.
- [90] Aytuğ Onan. Srl-aco: A text augmentation framework based on semantic role labeling and ant colony optimization. Journal of King Saud University-Computer and Information Sciences, 35(7):101611, 2023.
- [91] Enrica Troiano, Aswathy Velutharambath, and Roman Klinger. From theories on styles to their transfer in text: Bridging the gap with a hierarchical survey. *Natural Language Engineering*, 29(4):849–908, 2023.
- [92] Yiheng Liu, Tianle Han, Siyuan Ma, Jiayue Zhang, Yuanyuan Yang, Jiaming Tian, Hao He, Antong Li, Mengshen He, Zhengliang Liu, et al. Summary of chatgpt-related research and perspective towards the future of large language models. Meta-Radiology, page 100017, 2023.
- [93] Mahbubul Alam, Manar D Samad, Lasitha Vidyaratne, Alexander Glandon, and Khan M Iftekharuddin. Survey on deep neural networks in speech and vision systems. *Neurocomputing*, 417:302–321, 2020.
- [94] Wahab Khan, Ali Daud, Khairullah Khan, Shakoor Muhammad, and Rafiul Haq. Exploring the frontiers of deep learning and natural language processing: A comprehensive overview of key challenges and emerging trends. Natural Language Processing Journal, page 100026, 2023.
- [95] Abdullah M Braik and Maria Koliou. Automated building damage assessment and large-scale mapping by integrating satellite imagery, gis, and deep learning. *Computer-Aided Civil and Infrastructure Engineering*, 2024.
- [96] Zitu Zuo, Yongjie Niu, Jiale Li, Hongpeng Fu, and Mengjie Zhou. Machine learning for advanced emission monitoring and reduction strategies in fossil fuel power plants. Applied Sciences, 14(18):8442, 2024.
- [97] Mohaimenul Azam Khan Raiaan, Md Saddam Hossain Mukta, Kaniz Fatema, Nur Mohammad Fahad, Sadman Sakib, Most Marufatul Jannat Mim, Jubaer Ahmad, Mohammed Eunus Ali, and Sami Azam. A review on large language models: Architectures, applications, taxonomies, open issues and challenges. IEEE Access, 2024.

[98] Shengyun Wei, Shun Zou, Feifan Liao, et al. A comparison on data augmentation methods based on deep learning for audio classification. In *Journal of physics: Conference series*, volume 1453, page 012085. IOP Publishing, 2020.

- [99] Ariel Cohen, Inbal Rimon, Eran Aflalo, and Haim H Permuter. A study on data augmentation in voice anti-spoofing. Speech Communication, 141:56–67, 2022.
- [100] George Zhou, Yunchan Chen, and Candace Chien. On the analysis of data augmentation methods for spectral imaged based heart sound classification using convolutional neural networks. *BMC medical informatics and decision making*, 22(1):226, 2022.
- [101] Swarajya Madhuri Rayavarapu, Tammineni Shanmukha Prasanthi, Sasibhushana Rao Gottapu, and Aruna Singam. A comprehensive overview on data augmentation techniques for medical images. In 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC), pages 1324–1329. IEEE, 2024.
- [102] Huinian Li, Baoyu Chen, Jingjia Chen, Shuting Li, Feiyong He, and Hu Yingbiao. Itimca: Image-text information and cross-attention for multi-modal cassava leaf disease classification based on a novel multi-modal dataset in natural environments. *Crop Protection*, page 106981, 2024.
- [103] Ranjan Sapkota, Zhichao Meng, and Manoj Karkee. Synthetic meets authentic: Leveraging llm generated datasets for yolo11 and yolov10-based apple detection through machine vision sensors. Smart Agricultural Technology, page 100614, 2024.
- [104] Yang Liu, Yiqi Zhu, Zhehao Gu, Jinshan Pan, Juncheng Li, Ming Fan, Lihua Li, and Tieyong Zeng. Enhanced dual contrast representation learning with cell separation and merging for breast cancer diagnosis. *Computer Vision and Image Understanding*, 247:104065, 2024.
- [105] Daniil Kirilenko, Anton Andreychuk, Aleksandr I Panov, and Konstantin Yakovlev. Generative models for grid-based and image-based pathfinding. Artificial Intelligence, page 104238, 2024.
- [106] Jiajia Li, Zhouyu Guan, Jing Wang, Carol Y Cheung, Yingfeng Zheng, Lee-Ling Lim, Cynthia Ciwei Lim, Paisan Ruamviboonsuk, Rajiv Raman, Leonor Corsino, et al. Integrated image-based deep learning and language models for primary diabetes care. *Nature medicine*, pages 1–11, 2024.
- [107] Fenglin Liu, Tingting Zhu, Xian Wu, Bang Yang, Chenyu You, Chenyang Wang, Lei Lu, Zhangdaihong Liu, Yefeng Zheng, Xu Sun, et al. A medical multimodal large language model for future pandemics. NPJ Digital Medicine, 6(1): 226, 2023.
- [108] Nitesh Jindal, Prasanna Kumar Kumaresan, Rahul Ponnusamy, Sajeetha Thavareesan, Saranya Rajiakodi, and Bharathi Raja Chakravarthi. Mistra: Misogyny detection through text-image fusion and representation analysis. Natural Language Processing Journal, 7:100073, 2024.
- [109] Ranjan Sapkota, Achyut Paudel, and Manoj Karkee. Zero-shot automatic annotation and instance segmentation using llm-generated datasets: Eliminating field imaging and manual annotation for deep learning model development. arXiv preprint arXiv:2411.11285, 2024.
- [110] Ranjan Sapkota and Manoj Karkee. Improved yolov12 with llm-generated synthetic data for enhanced apple detection and benchmarking against yolov11 and yolov10. arXiv preprint arXiv:2503.00057, 2025.
- [111] Ranjan Sapkota, Zhichao Meng, Martin Churuvija, Xiaoqiang Du, Zenghong Ma, and Manoj Karkee. Comprehensive performance evaluation of yolov12, yolov10, yolov10, yolov9 and yolov8 on detecting and counting fruitlet in complex orchard environments. arXiv preprint arXiv:2407.12040, 2024.
- [112] Jiayi Yuan, Ruixiang Tang, Xiaoqian Jiang, and Xia Hu. Large language models for healthcare data augmentation: An example on patient-trial matching. In *AMIA Annual Symposium Proceedings*, volume 2023, page 1324. American Medical Informatics Association, 2023.
- [113] Kévin Cortacero, Brienne McKenzie, Sabina Müller, Roxana Khazen, Fanny Lafouresse, Gaëlle Corsaut, Nathalie Van Acker, François-Xavier Frenois, Laurence Lamant, Nicolas Meyer, et al. Evolutionary design of explainable algorithms for biomedical image segmentation. *Nature communications*, 14(1):7112, 2023.
- [114] Santhosh Raminedi, S Shridevi, and Daehan Won. Multi-modal transformer architecture for medical image analysis and automated report generation. Scientific Reports, 14(1):19281, 2024.
- [115] Yuxiang Wang, Xin Shi, and Xueqing Zhao. Mllm4rec: multimodal information enhancing llm for sequential recommendation. *Journal of Intelligent Information Systems*, pages 1–17, 2024.
- [116] Miruna Beţianu, Abele Mălan, Marco Aldinucci, Robert Birke, and Lydia Chen. Dallmi: Domain adaption for Ilm-based multi-label classifier. In Pacific-Asia Conference on Knowledge Discovery and Data Mining, pages 277–289. Springer, 2024.
- [117] Reshma Sheik, KP Siva Sundara, and S Jaya Nirmala. Neural data augmentation for legal overruling task: Small deep learning models vs. large language models. Neural Processing Letters, 56(2):121, 2024.
- [118] Ming Tao, Hao Tang, Fei Wu, Xiao-Yuan Jing, Bing-Kun Bao, and Changsheng Xu. Df-gan: A simple and effective baseline for text-to-image synthesis. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 16515–16525, 2022.

- [119] Youwei Liang, Junfeng He, Gang Li, Peizhao Li, Arseniy Klimovskiy, Nicholas Carolan, Jiao Sun, Jordi Pont-Tuset, Sarah Young, Feng Yang, et al. Rich human feedback for text-to-image generation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 19401–19411, 2024.
- [120] Quynh Phung, Songwei Ge, and Jia-Bin Huang. Grounded text-to-image synthesis with attention refocusing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7932–7942, 2024.
- [121] Morgan Heisler, Amin Banitalebi-Dehkordi, and Yong Zhang. Semaug: Semantically meaningful image augmentations for object detection through language grounding. In *European Conference on Computer Vision*, pages 610–626. Springer, 2022
- [122] Kyuheon Jung, Yongdeuk Seo, Seongwoo Cho, Jaeyoung Kim, Hyun-seok Min, and Sungchul Choi. Dalda: Data augmentation leveraging diffusion model and llm with adaptive guidance scaling. arXiv preprint arXiv:2409.16949, 2024
- [123] Tianhe Yu, Ted Xiao, Austin Stone, Jonathan Tompson, Anthony Brohan, Su Wang, Jaspiar Singh, Clayton Tan, Jodilyn Peralta, Brian Ichter, et al. Scaling robot learning with semantically imagined experience. arXiv preprint arXiv:2302.11550, 2023.
- [124] Noam Rotstein, David Bensaïd, Shaked Brody, Roy Ganz, and Ron Kimmel. Fusecap: Leveraging large language models for enriched fused image captions. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 5689–5700, 2024.
- [125] Jingru Yi, Burak Uzkent, Oana Ignat, Zili Li, Amanmeet Garg, Xiang Yu, and Linda Liu. Augment the pairs: Semantics-preserving image-caption pair augmentation for grounding-based vision and language models. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 5520–5530, 2024.
- [126] Sahand Sharifzadeh, Christos Kaplanis, Shreya Pathak, Dharshan Kumaran, Anastasija Ilic, Jovana Mitrovic, Charles Blundell, and Andrea Banino. Synth2: Boosting visual-language models with synthetic captions and image embeddings. arXiv preprint arXiv:2403.07750, 2024.
- [127] Jing Yu Koh, Daniel Fried, and Russ R Salakhutdinov. Generating images with multimodal language models. Advances in Neural Information Processing Systems, 36, 2024.
- [128] Wei Li, Xue Xu, Jiachen Liu, and Xinyan Xiao. Unimo-g: Unified image generation through multimodal conditional diffusion. arXiv preprint arXiv:2401.13388, 2024.
- [129] Oren Sultan, Alex Khasin, Guy Shiran, Asnat Greenstein-Messica, and Dafna Shahaf. Visual editing with llm-based tool chaining: An efficient distillation approach for real-time applications. arXiv preprint arXiv:2410.02952, 2024.
- [130] Jiawei Li, Fanrui Zhang, Jiaying Zhu, Esther Sun, Qiang Zhang, and Zheng-Jun Zha. Forgerygpt: Multimodal large language model for explainable image forgery detection and localization. arXiv preprint arXiv:2410.10238, 2024.
- [131] Wangyu Wu, Xianglin Qiu, Siqi Song, Zhenhong Chen, Xiaowei Huang, Fei Ma, and Jimin Xiao. Image augmentation agent for weakly supervised semantic segmentation. arXiv preprint arXiv:2412.20439, 2024.
- [132] Steven Song, Anirudh Subramanyam, Irene Madejski, and Robert L Grossman. Lab-rag: Label boosted retrieval augmented generation for radiology report generation. arXiv preprint arXiv:2411.16523, 2024.
- [133] Tobias Lingenberg, Markus Reuter, Gopika Sudhakaran, Dominik Gojny, Stefan Roth, and Simone Schaub-Meyer. Diagen: Diverse image augmentation with generative models. arXiv preprint arXiv:2408.14584, 2024.
- [134] Shukang Yin, Chaoyou Fu, Sirui Zhao, Yunhang Shen, Chunjiang Ge, Yan Yang, Zuwei Long, Yuhan Dai, Tong Xu, Xing Sun, et al. T2vid: Translating long text into multi-image is the catalyst for video-llms. arXiv preprint arXiv:2411.19951, 2024.
- [135] Jihao Liu, Xin Huang, Jinliang Zheng, Boxiao Liu, Jia Wang, Osamu Yoshie, Yu Liu, and Hongsheng Li. Mm-instruct: Generated visual instructions for large multimodal model alignment. arXiv preprint arXiv:2406.19736, 2024.
- [136] Chihcheng Hsieh, Catarina Moreira, Isabel Blanco Nobre, Sandra Costa Sousa, Chun Ouyang, Margot Brereton, Joaquim Jorge, and Jacinto C Nascimento. Dall-m: Context-aware clinical data augmentation with llms. arXiv preprint arXiv:2407.08227, 2024.
- [137] Yuhang Zang, Wei Li, Jun Han, Kaiyang Zhou, and Chen Change Loy. Contextual object detection with multimodal large language models. *International Journal of Computer Vision*, pages 1–19, 2024.
- [138] Aditya Ganeshan, Ryan Y. Huang, Xianghao Xu, R. Kenny Jones, and Daniel Ritchie. Parsel: Parameterized shape editing with language, 2024. URL https://arxiv.org/abs/2405.20319.
- [139] Charles R. Qi, Li Yi, Hao Su, and Leonidas J. Guibas. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In *Advances in Neural Information Processing Systems (NeurIPS)*, pages 5105–5114, 2017.
- [140] Yue Wang, Yongbin Sun, Ziwei Liu, Sanjay E. Sarasua, Michael M. Bronstein, and Justin M. Solomon. Dynamic graph cnn for learning on point clouds. In *ACM Transactions on Graphics (TOG)*, volume 38, pages 1–12, 2019.
- [141] Panos Achlioptas, Olga Diamanti, Ioannis Mitliagkas, and Leonidas Guibas. Learning representations and generative models for 3d point clouds. In *International Conference on Machine Learning (ICML)*, pages 40–49, 2018.
- [142] Weikai Chen, Kai Xu, et al. Deep part-aware shape editing for 3d point clouds. In *International Conference on 3D Vision (3DV)*, pages 438–447, 2021.

[143] Zhihao Fan and Xiaojun Wu. Sgpr: Segmentation-guided point cloud reconstruction for rotated objects. In *IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1465–1474, 2021.

- [144] Jiajun Wu, Chengkai Zhang, Tianfan Xue, William T. Freeman, and Joshua B. Tenenbaum. Learning a probabilistic latent space of object shapes via 3d generative-adversarial modeling. In *Advances in Neural Information Processing Systems (NeurIPS)*, pages 82–90, 2016.
- [145] Diego Valsesia, Giulia Fracastoro, and Enrico Magli. Learning localized generative models for 3d point clouds via graph convolution. In *International Conference on Learning Representations (ICLR)*, 2020.
- [146] Bo Zhou, Yuan Li, Yijun Li, et al. 3d generative adversarial models with diffusion-based methods. In *International Conference on 3D Vision (3DV)*, pages 191–202, 2021.
- [147] Jinliang Luo, Qingyong Hu, Andrew Markham, and Leonidas Guibas. Score-based generative models for 3d point cloud generation and editing. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 5527–5537, 2023
- [148] Min-Gyu Kim, Sanghyun Park, Gyeongsik Kwon, Hyunwoo Park, and Kyoung Mu Lee Kim. Text2mesh: Text-driven neural stylization for meshes and point clouds. In *ACM SIGGRAPH Asia*, pages 1–10, 2022.
- [149] Alex Nichol, Aditya Ramesh, and Prafulla Dhariwal. Point-e: A system for generating 3d point clouds from complex prompts. OpenAI Technical Report, 2022. https://github.com/openai/point-e.
- [150] Heewoo Jun, Robin Rombach, Andreas Blattmann, Lucas Beyer, Bjorn Ommer, Tim Salimans, and Ilya Sutskever. Shap-e: Generating conditional 3d implicit functions. OpenAI Technical Report, 2023.
- [151] Ben Poole, Ajay Jalal, Jonathan T. Barron, et al. Dreamfusion: Text-to-3d using 2d diffusion. Google Research Preprint, 2022. https://dreamfusion3d.github.io/.
- [152] Fangzhou Liu, Pengsong Liu, et al. Zero-1-to-3: Zero-shot one image to 3d object. arXiv preprint arXiv:2303.11328, 2023.
- [153] Yifan Li, Lin Shao, and Bin Yang. Shapepart: Learning region-level decompositions of 3d objects via part-aware shape synthesis. In IEEE International Conference on Computer Vision (ICCV), pages 1241–1250, 2021.
- [154] Wei Wu, Fangfei Xiang, and Zhen Li. Pq-net: A generative part quality network for 3d shape composition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4902–4911, 2021.
- [155] Yang Su, Qing Liu, and Song-Chun Zhu. Semanticpc: Semantic-driven part composition for 3d object generation. In Conference on Computer Vision and Pattern Recognition (CVPR), pages 21334–21343, 2023.
- [156] Haoyang Wu, Boqing Chen, Xi Li, and Takashi Sato. Det3d: Multimodal 3d detection with point clouds, images, and language prompts. In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2023.
- [157] Hengshuang Zhao, Li Yi, Leonidas Guibas, and Jiaya Jia. Foundations3d: Large-scale pretraining of 3d vision-language models via foundational shapes and descriptions. In *International Conference on Machine Learning (ICML)*, pages 8487–8501, 2023.
- [158] Linmei Hu, Hongyu He, Duokang Wang, Ziwang Zhao, Yingxia Shao, and Liqiang Nie. Llm vs small model? large language model based text augmentation enhanced personality detection model. In *Proceedings of the AAAI Conference* on Artificial Intelligence, volume 38, pages 18234–18242, 2024.
- [159] Shih-Lun Wu, Xuankai Chang, Gordon Wichern, Jee-weon Jung, François Germain, Jonathan Le Roux, and Shinji Watanabe. Improving audio captioning models with fine-grained audio features, text embedding supervision, and Ilm mix-up augmentation. In ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 316–320. IEEE, 2024.
- [160] Huanhuan Zhao, Haihua Chen, Thomas A Ruggles, Yunhe Feng, Debjani Singh, and Hong-Jun Yoon. Improving text classification with large language model-based data augmentation. *Electronics*, 13(13):2535, 2024.
- [161] Vitor Gaboardi dos Santos, Guto Leoni Santos, Theo Lynn, and Boualem Benatallah. Identifying citizen-related issues from social media using llm-based data augmentation. In *International Conference on Advanced Information Systems Engineering*, pages 531–546. Springer, 2024.
- [162] Jiaheng Hua, Xiaodong Cui, Xianghua Li, Keke Tang, and Peican Zhu. Multimodal fake news detection through data augmentation-based contrastive learning. Applied Soft Computing, 136:110125, 2023.
- [163] Jianqiao Lai, Xinran Yang, Wenyue Luo, Linjiang Zhou, Langchen Li, Yongqi Wang, and Xiaochuan Shi. Rumorllm: A rumor large language model-based fake-news-detection data-augmentation approach. Applied Sciences, 14(8):3532, 2024.
- [164] Jing Zhang, Hui Gao, Peng Zhang, Boda Feng, Wenmin Deng, and Yuexian Hou. La-ucl: Llm-augmented unsupervised contrastive learning framework for few-shot text classification. In Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024), pages 10198–10207, 2024.
- [165] Meishan Zhang, Gongyao Jiang, Shuang Liu, Jing Chen, and Min Zhang. Llm-assisted data augmentation for chinese dialogue–level dependency parsing. *Computational Linguistics*, pages 1–24, 2024.
- [166] Mengting Wan, Tara Safavi, Sujay Kumar Jauhar, Yujin Kim, Scott Counts, Jennifer Neville, Siddharth Suri, Chirag Shah, Ryen W White, Longqi Yang, et al. Tnt-llm: Text mining at scale with large language models. In Proceedings of

- the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pages 5836–5847, 2024.
- [167] Xunxin Cai, Meng Xiao, Zhiyuan Ning, and Yuanchun Zhou. Resolving the imbalance issue in hierarchical disciplinary topic inference via llm-based data augmentation. In 2023 IEEE International Conference on Data Mining Workshops (ICDMW), pages 1424–1429. IEEE, 2023.
- [168] Jiayi Yuan, Ruixiang Tang, Xiaoqian Jiang, and Xia Hu. Llm for patient-trial matching: Privacy-aware data augmentation towards better performance and generalizability. In American Medical Informatics Association (AMIA) Annual Symposium, 2023.
- [169] Atif Latif and Jihie Kim. Evaluation and analysis of large language models for clinical text augmentation and generation. IEEE Access, 2024.
- [170] Toufique Ahmed, Kunal Suresh Pai, Premkumar Devanbu, and Earl Barr. Automatic semantic augmentation of language model prompts (for code summarization). In *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering*, pages 1–13, 2024.
- [171] Zihao Meng, Tao Liu, Heng Zhang, Kai Feng, and Peng Zhao. Cean: Contrastive event aggregation network with llm-based augmentation for event extraction. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 321–333, 2024.
- [172] Mustafa Çataltaş, Nurdan Akhan Baykan, and Ilyas Cicekli. Comparison of textual data augmentation methods on sst-2 dataset. In *International Congress of Electrical and Computer Engineering*, pages 189–201. Springer, 2023.
- [173] Nicolas Antonio Cloutier and Nathalie Japkowicz. Fine-tuned generative llm oversampling can improve performance over traditional techniques on multiclass imbalanced text classification. In 2023 IEEE International Conference on Big Data (BigData), pages 5181–5186. IEEE, 2023.
- [174] Haein Jung, Heuiyeen Yeen, Jeehyun Lee, Minju Kim, Namo Bang, and Myoung-Wan Koo. Enhancing task-oriented dialog system with subjective knowledge: A large language model-based data augmentation framework. In Proceedings of The Eleventh Dialog System Technology Challenge, pages 150–165, 2023.
- [175] Kanishka Silva, Ingo Frommholz, Burcu Can, Fred Blain, Raheem Sarwar, and Laura Ugolini. Forged-gan-bert: Authorship attribution for llm-generated forged novels. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 325–337, 2024.
- [176] Zhuo Deng, Weihao Gao, Chucheng Chen, Zhiyuan Niu, Zheng Gong, Ruiheng Zhang, Zhenjie Cao, Fang Li, Zhaoyi Ma, Wenbin Wei, et al. Ophglm: An ophthalmology large language-and-vision assistant. Artificial Intelligence in Medicine, 157:103001, 2024.
- [177] Anna Glazkova and Olga Zakharova. Evaluating llm prompts for data augmentation in multi-label classification of ecological texts. arXiv preprint arXiv:2411.14896, 2024.
- [178] Lukas Fischer, Yingqiang Gao, Alexa Lintner, and Sarah Ebling. Swissadt: An audio description translation system for swiss languages. arXiv preprint arXiv:2411.14967, 2024.
- [179] Haixing Dai, Zhengliang Liu, Wenxiong Liao, Xiaoke Huang, Yihan Cao, Zihao Wu, Lin Zhao, Shaochen Xu, Wei Liu, Ninghao Liu, et al. Auggpt: Leveraging chatgpt for text data augmentation. arXiv preprint arXiv:2302.13007, 2023.
- [180] Nicholas Lee, Thanakul Wattanawong, Sehoon Kim, Karttikeya Mangalam, Sheng Shen, Gopala Anumanchipalli, Michael W Mahoney, Kurt Keutzer, and Amir Gholami. Llm2llm: Boosting llms with novel iterative data enhancement. arXiv preprint arXiv:2403.15042, 2024.
- [181] Zichen Wen, Dadi Guo, and Huishuai Zhang. Aidbench: A benchmark for evaluating the authorship identification capability of large language models. *arXiv preprint arXiv:2411.13226*, 2024.
- [182] Andrea Kang, Jun Yu Chen, Zoe Lee-Youngzie, and Shuhao Fu. Synthetic data generation with llm for improved depression prediction. *arXiv preprint arXiv:2411.17672*, 2024.
- [183] Jan Cegin, Jakub Simko, and Peter Brusilovsky. Llms vs established text augmentation techniques for classification: When do the benefits outweight the costs? arXiv preprint arXiv:2408.16502, 2024.
- [184] Zaid Alyafeai, Michael Pieler, Hannah Teufel, Jonathan Tow, Marco Bellagente, Duy Phung, Nikhil Pinnaparaju, Reshinth Adithyan, Paulo Rocha, Maksym Zhuravinskyi, et al. Arabic stable lm: Adapting stable lm 2 1.6 b to arabic. arXiv preprint arXiv:2412.04277, 2024.
- [185] Ori Yoran, Tomer Wolfson, Ori Ram, and Jonathan Berant. Making retrieval-augmented language models robust to irrelevant context. *arXiv preprint arXiv:2310.01558*, 2023.
- [186] You-Qian Lee, Ching-Tai Chen, Chien-Chang Chen, Chung-Hong Lee, Peitsz Chen, Chi-Shin Wu, and Hong-Jie Dai. Unlocking the secrets behind advanced artificial intelligence language models in deidentifying chinese-english mixed clinical text: Development and validation study. *Journal of Medical Internet Research*, 26:e48443, 2024.
- [187] Chenxi Whitehouse, Monojit Choudhury, and Alham Fikri Aji. Llm-powered data augmentation for enhanced cross-lingual performance. arXiv preprint arXiv:2305.14288, 2023.
- [188] Bonan Min, Hayley Ross, Elior Sulem, Amir Pouran Ben Veyseh, Thien Huu Nguyen, Oscar Sainz, Eneko Agirre, Ilana Heintz, and Dan Roth. Recent advances in natural language processing via large pre-trained language models: A survey. ACM Computing Surveys, 56(2):1–40, 2023.

[189] Manish Gupta and Puneet Agrawal. Compression of deep learning models for text: A survey. ACM Transactions on Knowledge Discovery from Data (TKDD), 16(4):1–55, 2022.

- [190] Pierre Vilar Dantas, Waldir Sabino da Silva Jr, Lucas Carvalho Cordeiro, and Celso Barbosa Carvalho. A comprehensive review of model compression techniques in machine learning. *Applied Intelligence*, 54(22):11804–11844, 2024.
- [191] Junchao Wu, Shu Yang, Runzhe Zhan, Yulin Yuan, Lidia Sam Chao, and Derek Fai Wong. A survey on llm-generated text detection: Necessity, methods, and future directions. *Computational Linguistics*, pages 1–65, 2025.
- [192] Tohid Atashbar. Reinforcement learning from experience feedback: Application to economic policy. 2024.
- [193] Junjie Ye, Nuo Xu, Yikun Wang, Jie Zhou, Qi Zhang, Tao Gui, and Xuanjing Huang. Llm-da: Data augmentation via large language models for few-shot named entity recognition. arXiv preprint arXiv:2402.14568, 2024.
- [194] Ranjan Sapkota, Shaina Raza, and Manoj Karkee. Comprehensive analysis of transparency and accessibility of chatgpt, deepseek, and other sota large language models. arXiv preprint arXiv:2502.18505, 2025.
- [195] Bishwamittra Ghosh, Sarah Hasan, Naheed Anjum Arafat, and Arijit Khan. Logical consistency of large language models in fact-checking. arXiv preprint arXiv:2412.16100, 2024.
- [196] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, et al. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. ACM Transactions on Information Systems, 2023.
- [197] Yinhong Liu, Zhijiang Guo, Tianya Liang, Ehsan Shareghi, Ivan Vulić, and Nigel Collier. Aligning with logic: Measuring, evaluating and improving logical consistency in large language models. arXiv preprint arXiv:2410.02205, 2024
- [198] Quinten Bolding, Baohao Liao, Brandon James Denis, Jun Luo, and Christof Monz. Ask language model to clean your noisy translation data. arXiv preprint arXiv:2310.13469, 2023.
- [199] Han Yin, Yang Xiao, Jisheng Bai, and Rohan Kumar Das. Leveraging llm and text-queried separation for noise-robust sound event detection. *arXiv preprint arXiv:2411.01174*, 2024.
- [200] Yue Yu, Yuchen Zhuang, Jieyu Zhang, Yu Meng, Alexander J Ratner, Ranjay Krishna, Jiaming Shen, and Chao Zhang. Large language model as attributed training data generator: A tale of diversity and bias. Advances in Neural Information Processing Systems, 36, 2024.
- [201] Kyungmin Kim, SangHun Im, GiBaeg Kim, and Heung-Seon Oh. Tardis: Text augmentation for refining diversity and separability. arXiv preprint arXiv:2501.02739, 2025.
- [202] Jan Cegin, Branislav Pecher, Jakub Simko, Ivan Srba, Maria Bielikova, and Peter Brusilovsky. Effects of diversity incentives on sample diversity and downstream model performance in llm-based text augmentation. *arXiv preprint arXiv:2401.06643*, 2024.
- [203] Zhixi Cai, Shreya Ghosh, Aman Pankaj Adatia, Munawar Hayat, Abhinav Dhall, Tom Gedeon, and Kalin Stefanov. Av-deepfake1m: A large-scale llm-driven audio-visual deepfake dataset. In Proceedings of the 32nd ACM International Conference on Multimedia, pages 7414–7423, 2024.
- [204] Priyanshu Dhingra, Satyam Agrawal, Chandra Sekar Veerappan, Thi Nga Ho, Eng Siong Chng, and Rong Tong. Speech de-identification data augmentation leveraging large language model. In 2024 International Conference on Asian Language Processing (IALP), pages 97–102. IEEE, 2024.
- [205] Priyanshu Dhingra, Satyam Agrawal, Chandra Sekar Veerappan, Eng Siong Chng, and Rong Tong. Enhancing speech de-identification with llm-based data augmentation. In 2024 11th International Conference on Advanced Informatics: Concept, Theory and Application (ICAICTA), pages 1–5. IEEE, 2024.
- [206] Ziyang Ma, Wen Wu, Zhisheng Zheng, Yiwei Guo, Qian Chen, Shiliang Zhang, and Xie Chen. Leveraging speech ptm, text llm, and emotional tts for speech emotion recognition. In *ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 11146–11150. IEEE, 2024.
- [207] David Xu. Audiosetmix: Enhancing audio-language datasets with llm-assisted augmentations. arXiv preprint arXiv:2405.11093, 2024.
- [208] Sreyan Ghosh, Sonal Kumar, Zhifeng Kong, Rafael Valle, Bryan Catanzaro, and Dinesh Manocha. Synthio: Augmenting small-scale audio classification datasets with synthetic data. arXiv preprint arXiv:2410.02056, 2024.
- [209] Ahmed Heakl, Youssef Zaghloul, Mennatullah Ali, Rania Hossam, and Walid Gomaa. Arzen-llm: Code-switched egyptian arabic-english translation and speech recognition using llms. Procedia Computer Science, 244:113–120, 2024.
- [210] Ehtesham Hashmi, Sule Yildirim Yayilgan, Muhammad Mudassar Yamin, Mohamed Abomhara, and Mohib Ullah. Self-supervised hate speech detection in norwegian texts with lexical and semantic augmentations. Expert Systems with Applications, page 125843, 2024.
- [211] Fang Xu, Tianyu Zhou, Tri Nguyen, Haohui Bao, Christine Lin, and Jing Du. Integrating augmented reality and Ilm for enhanced cognitive support in critical audio communications. *International Journal of Human-Computer Studies*, page 103402, 2024.
- [212] Alec Cook and Oktay Karakuş. Llm-commentator: Novel fine-tuning strategies of large language models for automatic commentary generation using football event data. *Knowledge-Based Systems*, 300:112219, 2024.

- [213] Christos Gkournelos, Christos Konstantinou, and Sotiris Makris. An llm-based approach for enabling seamless human-robot collaboration in assembly. *CIRP Annals*, 2024.
- [214] Marc Alier, Juanan Pereira, Francisco José García-Peñalvo, Maria Jose Casañ, and Jose Cabré. Lamb: An open-source software framework to create artificial intelligence assistants deployed and integrated into learning management systems. *Computer Standards & Interfaces*, 92:103940, 2025.
- [215] A Senthilselvi, RP Prawin, V Harshit, et al. Abstractive summarization of youtube videos using lamini-flan-t5 llm. In 2024 Second International Conference on Advances in Information Technology (ICAIT), volume 1, pages 1–5. IEEE, 2024.
- [216] Mingqiu Wang, Izhak Shafran, Hagen Soltau, Wei Han, Yuan Cao, Dian Yu, and Laurent El Shafey. Retrieval augmented end-to-end spoken dialog models. In ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 12056–12060. IEEE, 2024.
- [217] Pengcheng Qiu, Chaoyi Wu, Xiaoman Zhang, Weixiong Lin, Haicheng Wang, Ya Zhang, Yanfeng Wang, and Weidi Xie. Towards building multilingual language model for medicine. *Nature Communications*, 15(1):8384, 2024.
- [218] Koki Hasebe, Shintaro Fujimura, Tsuyoshi Kojima, Keiichi Tamura, Yoshitaka Kawai, Yo Kishimoto, and Koichi Omori. The effect of noise on deep learning for classification of pathological voice. The Laryngoscope, 134(8):3537–3541, 2024.
- [219] Arvind Krishna Sridhar, Yinyi Guo, and Erik Visser. Enhancing temporal understanding in audio question answering for large audio language models. arXiv preprint arXiv:2409.06223, 2024.
- [220] Zhihong Lei, Xingyu Na, Mingbin Xu, Ernest Pusateri, Christophe Van Gysel, Yuanyuan Zhang, Shiyi Han, and Zhen Huang. Contextualization of asr with llm using phonetic retrieval-based augmentation. arXiv preprint arXiv:2409.15353, 2024
- [221] Arushi Goel, Zhifeng Kong, Rafael Valle, and Bryan Catanzaro. Audio dialogues: Dialogues dataset for audio and music understanding. arXiv preprint arXiv:2404.07616, 2024.
- [222] Dongchao Yang, Jinchuan Tian, Xu Tan, Rongjie Huang, Songxiang Liu, Xuankai Chang, Jiatong Shi, Sheng Zhao, Jiang Bian, Xixin Wu, et al. Uniaudio: An audio foundation model toward universal audio generation. *arXiv preprint arXiv:2310.00704*, 2023.
- [223] Zixuan Wang, Yu-Wing Tai, and Chi-Keung Tang. Audio-agent: Leveraging llms for audio generation, editing and composition. arXiv preprint arXiv:2410.03335, 2024.
- [224] Christine Cuskley, Rebecca Woods, and Molly Flaherty. The limitations of large language models for understanding human language and cognition. *Open Mind*, 8:1058–1083, 2024.
- [225] Do Hyun Lee, Yoonah Song, and Hong Kook Kim. Performance improvement of language-queried audio source separation based on caption augmentation from large language models for dcase challenge 2024 task 9. arXiv preprint arXiv:2406.11248, 2024.
- [226] Tanmay Srivastava, Prerna Khanna, Shijia Pan, Phuc Nguyen, and Shubham Jain. Unvoiced: Designing an Ilm-assisted unvoiced user interface using earables. In Proceedings of the 22nd ACM Conference on Embedded Networked Sensor Systems, pages 784–798, 2024.
- [227] Hamza Kheddar, Mustapha Hemis, and Yassine Himeur. Automatic speech recognition using advanced deep learning approaches: A survey. *Information Fusion*, page 102422, 2024.
- [228] Zhaowei Li, Qi Xu, Dong Zhang, Hang Song, Yiqing Cai, Qi Qi, Ran Zhou, Junting Pan, Zefeng Li, Vu Tu, et al. Groundingspt: Language enhanced multi-modal grounding model. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6657–6678, 2024.
- [229] Yuanyuan Zhu, Jiaxu He, Ruihao Jing, Yaodong Song, Jie Lian, Xiao-lei Zhang, and Jie Li. Llm-based expressive text-to-speech synthesizer with style and timbre disentanglement. In 2024 IEEE 14th International Symposium on Chinese Spoken Language Processing (ISCSLP), pages 596–600. IEEE, 2024.
- [230] Kate Heidemann. A system for describing vocal timbre in popular song. Music Theory Online, 22(1), 2016.
- [231] Albrecht Schneider. Perception of timbre and sound color. Springer Handbook of Systematic Musicology, pages 687–725, 2018.
- [232] Sijing Chen, Yuan Feng, Laipeng He, Tianwei He, Wendi He, Yanni Hu, Bin Lin, Yiting Lin, Yu Pan, Pengfei Tan, et al. Takin: A cohort of superior quality zero-shot speech generation models. arXiv preprint arXiv:2409.12139, 2024.
- [233] Zhen Ye, Peiwen Sun, Jiahe Lei, Hongzhan Lin, Xu Tan, Zheqi Dai, Qiuqiang Kong, Jianyi Chen, Jiahao Pan, Qifeng Liu, et al. Codec does matter: Exploring the semantic shortcoming of codec for audio language model. arXiv preprint arXiv:2408.17175, 2024.
- [234] Fabian Barreto, Lalita Moharkar, Madhura Shirodkar, Vidya Sarode, Saniya Gonsalves, and Aaron Johns. Generative artificial intelligence: Opportunities and challenges of large language models. In *International Conference on Intelligent Computing and Networking*, pages 545–553. Springer, 2023.
- [235] Zhenwei Zhang, Shengming Zhang, Dong Ni, Zhaoguo Wei, Kongjun Yang, Shan Jin, Gan Huang, Zhen Liang, Li Zhang, Linling Li, et al. Multimodal sensing for depression risk detection: integrating audio, video, and text data. Sensors, 24(12):3714, 2024.

[236] TA Mariya Celin, P Vijayalakshmi, and T Nagarajan. Data augmentation techniques for transfer learning-based continuous dysarthric speech recognition. *Circuits, Systems, and Signal Processing*, 42(1):601–622, 2023.

- [237] Yifan Peng, Krishna C Puvvada, Zhehuai Chen, Piotr Zelasko, He Huang, Kunal Dhawan, Ke Hu, Shinji Watanabe, Jagadeesh Balam, and Boris Ginsburg. Voicetextblender: Augmenting large language models with speech capabilities via single-stage joint speech-text supervised fine-tuning. arXiv preprint arXiv:2410.17485, 2024.
- [238] Andreas Nautsch, Abelino Jiménez, Amos Treiber, Jascha Kolberg, Catherine Jasserand, Els Kindt, Héctor Delgado, Massimiliano Todisco, Mohamed Amine Hmani, Aymen Mtibaa, et al. Preserving privacy in speaker and speech characterisation. Computer Speech & Language, 58:441–480, 2019.
- [239] Shengshan Hu, Xingcan Shang, Zhan Qin, Minghui Li, Qian Wang, and Cong Wang. Adversarial examples for automatic speech recognition: Attacks and countermeasures. IEEE Communications Magazine, 57(10):120–126, 2019.
- [240] Guangke Chen, Zhe Zhao, Fu Song, Sen Chen, Lingling Fan, Feng Wang, and Jiashui Wang. Towards understanding and mitigating audio adversarial examples for speaker recognition. *IEEE Transactions on Dependable and Secure Computing*, 20(5):3970–3987, 2022.
- [241] Songyue Han, Mingyu Wang, Jialong Zhang, Dongdong Li, and Junhong Duan. A review of large language models: Fundamental architectures, key technological evolutions, interdisciplinary technologies integration, optimization and compression techniques, applications, and challenges. *Electronics*, 13(24):5040, 2024.
- [242] Daniel Ogof, Anastasia Romanov, and Viktor Polanski. Enhancing audio comprehension in large language models: Integrating audio knowledge. *Authorea Preprints*, 2024.
- [243] Avihu Dekel, Slava Shechtman, Raul Fernandez, David Haws, Zvi Kons, and Ron Hoory. Speak while you think: Streaming speech synthesis during text generation. In *ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 11931–11935. IEEE, 2024.
- [244] Longwei Zheng, Fei Jiang, Xiaoqing Gu, Yuanyuan Li, Gong Wang, and Haomin Zhang. Teaching via llm-enhanced simulations: Authenticity and barriers to suspension of disbelief. The Internet and Higher Education, 65:100990, 2025.
- [245] David Ghiurău and Daniela Elena Popescu. Distinguishing reality from ai: Approaches for detecting synthetic content. Computers, 14(1):1, 2024.
- [246] Halit Bakır, Ayşe Nur Çayır, and Tuğba Selcen Navruz. A comprehensive experimental study for analyzing the effects of data augmentation techniques on voice classification. Multimedia Tools and Applications, 83(6):17601-17628, 2024.
- [247] Zohaib Mushtaq and Shun-Feng Su. Environmental sound classification using a regularized deep convolutional neural network with data augmentation. *Applied Acoustics*, 167:107389, 2020.
- [248] Siyuan Shen, Feng Liu, and Aimin Zhou. Mingling or misalignment? temporal shift for speech emotion recognition with pre-trained representations. In ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 1–5. IEEE, 2023.
- [249] Yassir Fathullah, Chunyang Wu, Egor Lakomkin, Ke Li, Junteng Jia, Yuan Shangguan, Jay Mahadeokar, Ozlem Kalinli, Christian Fuegen, and Mike Seltzer. Audiochatllama: Towards general-purpose speech abilities for llms. In Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pages 5522–5532, 2024.
- [250] Minh Duc Vu, Han Wang, Jieshan Chen, Zhuang Li, Shengdong Zhao, Zhenchang Xing, and Chunyang Chen. Gptvoicetasker: Advancing multi-step mobile task efficiency through dynamic interface exploration and learning. In *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*, pages 1–17, 2024.
- [251] Artemis Panagopoulou, Le Xue, Ning Yu, Junnan Li, Dongxu Li, Shafiq Joty, Ran Xu, Silvio Savarese, Caiming Xiong, and Juan Carlos Niebles. X-instructblip: A framework for aligning image, 3d, audio, video to llms and its emergent cross-modal reasoning. In European Conference on Computer Vision, pages 177–197. Springer, 2025.
- [252] Malay Kumar Majhi and Sujan Kumar Saha. An automatic speech recognition system in odia language using attention mechanism and data augmentation. *International Journal of Speech Technology*, 27(3):717–728, 2024.
- [253] Nick Rossenbach, Albert Zeyer, Ralf Schlüter, and Hermann Ney. Generating synthetic audio data for attention-based speech recognition systems. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7069-7073. IEEE, 2020.
- [254] Huiting Fan, Xingnan Zhang, Yingying Xu, Jiangxiong Fang, Shiqing Zhang, Xiaoming Zhao, and Jun Yu. Transformer-based multimodal feature enhancement networks for multimodal depression detection integrating video, audio and remote photoplethysmograph signals. *Information Fusion*, 104:102161, 2024.
- [255] Christoforos Kachris. A survey on hardware accelerators for large language models. Applied Sciences, 15(2):586, 2025.
- [256] Jinbo Wen, Ruichen Zhang, Dusit Niyato, Jiawen Kang, Hongyang Du, Yang Zhang, and Zhu Han. Generative ai for low-carbon artificial intelligence of things with large language models. IEEE Internet of Things Magazine, 8(1):82–91, 2024.
- [257] Sasha Luccioni, Yacine Jernite, and Emma Strubell. Power hungry processing: Watts driving the cost of ai deployment? In The 2024 ACM Conference on Fairness, Accountability, and Transparency, pages 85–99, 2024.

- [258] Ke Tan and DeLiang Wang. Towards model compression for deep learning based speech enhancement. *IEEE/ACM transactions on audio, speech, and language processing, 29:1785–1794, 2021.*
- [259] Danwei Cai and Ming Li. Leveraging asr pretrained conformers for speaker verification through transfer learning and knowledge distillation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2024.
- [260] Joo-Young Kim. Fpga based neural network accelerators. In Advances in Computers, volume 122, pages 135–165. Elsevier, 2021.
- [261] Peter Bell, Joachim Fainberg, Ondrej Klejch, Jinyu Li, Steve Renals, and Pawel Swietojanski. Adaptation algorithms for neural network-based speech recognition: An overview. *IEEE Open Journal of Signal Processing*, 2:33–66, 2020.
- [262] Bhuwan Bhattarai and Joonwhoan Lee. A comprehensive review on music transcription. *Applied Sciences*, 13(21): 11882, 2023.
- [263] Syed Irfan Ali Meerza, Jian Liu, and Lichao Sun. Harmonycloak: Making music unlearnable for generative ai. In 2025 IEEE Symposium on Security and Privacy (SP), pages 85–85. IEEE Computer Society, 2024.
- [264] Jing Peng, Yucheng Wang, Yu Xi, Xv Li, and Kai Yu. A survey on speech large language models. arXiv preprint arXiv:2410.18908, 2024.
- [265] EG Satish, P Ramesh Naidu, Girish Madhava Mogera, HV Karthik, et al. Voice over vision: A sequence-to-sequence model by text to speech technology. In 2024 First International Conference on Innovations in Communications, Electrical and Computer Engineering (ICICEC), pages 1–7. IEEE, 2024.
- [266] Zheyi Chen, Liuchang Xu, Hongting Zheng, Luyao Chen, Amr Tolba, Liang Zhao, Keping Yu, and Hailin Feng. Evolution and prospects of foundation models: From large language models to large multimodal models. Computers, Materials & Continua, 80(2), 2024.
- [267] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. arXiv preprint arXiv:2501.12948, 2025.
- [268] Rui Qian, Xin Yin, and Dejing Dou. Reasoning to attend: Try to understand how< seg> token works. arXiv preprint arXiv:2412.17741, 2024.
- [269] Jiandong Jin, Xiao Wang, Qian Zhu, Haiyang Wang, and Chenglong Li. Pedestrian attribute recognition: A new benchmark dataset and a large language model augmented framework. arXiv preprint arXiv:2408.09720, 2024.
- [270] Jinghui Liu and Anthony Nguyen. Rephrasing electronic health records for pretraining clinical language models. arXiv preprint arXiv:2411.18940, 2024.
- [271] Amar Abane, Anis Bekri, and Abdella Battou. Fastrag: Retrieval augmented generation for semi-structured data. arXiv preprint arXiv:2411.13773, 2024.
- [272] Mu Yang, Bowen Shi, Matthew Le, Wei-Ning Hsu, and Andros Tjandra. Audiobox tta-rag: Improving zero-shot and few-shot text-to-audio with retrieval-augmented generation. *arXiv preprint arXiv:2411.05141*, 2024.
- [273] Kazi Ahmed Asif Fuad and Lizhong Chen. Llm-ref: Enhancing reference handling in technical writing with large language models. arXiv preprint arXiv:2411.00294, 2024.
- [274] Zhenhua Wang, Guang Xu, and Ming Ren. Llm-generated natural language meets scaling laws: New explorations and data augmentation methods. arXiv preprint arXiv:2407.00322, 2024.
- [275] Yiping Song, Juhua Zhang, Zhiliang Tian, Yuxin Yang, Minlie Huang, and Dongsheng Li. Llm-based privacy data augmentation guided by knowledge distillation with a distribution tutor for medical text classification. arXiv preprint arXiv:2402.16515, 2024.
- [276] Haoran Yang, Xiangyu Zhao, Sirui Huang, Qing Li, and Guandong Xu. Latex-gcl: Large language models (llms)-based data augmentation for text-attributed graph contrastive learning. arXiv preprint arXiv:2409.01145, 2024.
- [277] Yizhu Liu, Ran Tao, Shengyu Guo, and Yifan Yang. Improving topic relevance model by mix-structured summarization and llm-based data augmentation. arXiv preprint arXiv:2404.02616, 2024.
- [278] Jan Cegin, Branislav Pecher, Jakub Simko, Ivan Srba, Maria Bielikova, and Peter Brusilovsky. Use random selection for now: Investigation of few-shot selection strategies in llm-based text augmentation for classification. arXiv preprint arXiv:2410.10756, 2024.
- [279] Kaidi Jia, Yanxia Wu, and Rongsheng Li. Curriculum-style data augmentation for llm-based metaphor detection. arXiv preprint arXiv:2412.02956, 2024.
- [280] Linda Zeng. Leveraging large language models for code-mixed data augmentation in sentiment analysis. arXiv preprint arXiv:2411.00691, 2024.
- [281] Onkar Litake, Niraj Yagnik, and Shreyas Labhsetwar. Inditext boost: Text augmentation for low resource india languages. arXiv preprint arXiv:2401.13085, 2024.
- [282] Gaurav Sahu, Olga Vechtomova, Dzmitry Bahdanau, and Issam H Laradji. Promptmix: A class boundary augmentation method for large language model distillation. arXiv preprint arXiv:2310.14192, 2023.
- [283] Arijit Ghosh Chowdhury and Aman Chadha. Generative data augmentation using llms improves distributional robustness in question answering. arXiv preprint arXiv:2309.06358, 2023.

[284] Leyao Wang, Yu Wang, Bo Ni, Yuying Zhao, and Tyler Derr. Large language model-based augmentation for imbalanced node classification on text-attributed graphs. arXiv preprint arXiv:2410.16882, 2024.

- [285] Deepanway Ghosal, Navonil Majumder, Ambuj Mehrish, and Soujanya Poria. Text-to-audio generation using instruction-tuned llm and latent diffusion model. arXiv preprint arXiv:2304.13731, 2023.
- [286] Ilaria Manco, Justin Salamon, and Oriol Nieto. Augment, drop & swap: Improving diversity in llm captions for efficient music-text representation learning. arXiv preprint arXiv:2409.11498, 2024.
- [287] Baihan Li, Zeyu Xie, Xuenan Xu, Yiwei Guo, Ming Yan, Ji Zhang, Kai Yu, and Mengyue Wu. Divesound: Llm-assisted automatic taxonomy construction for diverse audio generation. arXiv preprint arXiv:2407.13198, 2024.
- [288] Fangxun Shu, Lei Zhang, Hao Jiang, and Cihang Xie. Audio-visual llm for video understanding. arXiv preprint arXiv:2312.06720, 2023.
- [289] Jiawei Huang, Yi Ren, Rongjie Huang, Dongchao Yang, Zhenhui Ye, Chen Zhang, Jinglin Liu, Xiang Yin, Zejun Ma, and Zhou Zhao. Make-an-audio 2: Temporal-enhanced text-to-audio generation. arXiv preprint arXiv:2305.18474, 2023.
- [290] Hyunjong Ok, Suho Yoo, and Jaeho Lee. Audiobert: Audio knowledge augmented language model. arXiv preprint arXiv:2409.08199, 2024.
- [291] Yi Lu, Yuankun Xie, Ruibo Fu, Zhengqi Wen, Jianhua Tao, Zhiyong Wang, Xin Qi, Xuefei Liu, Yongwei Li, Yukun Liu, et al. Codecfake: An initial dataset for detecting llm-based deepfake audio. arXiv preprint arXiv:2406.08112, 2024.
- [292] Nilaksh Das, Saket Dingliwal, Srikanth Ronanki, Rohit Paturi, Zhaocheng Huang, Prashant Mathur, Jie Yuan, Dhanush Bekal, Xing Niu, Sai Muralidhar Jayanthi, et al. Speechverse: A large-scale generalizable audio language model. arXiv preprint arXiv:2405.08295, 2024.
- [293] Théophane Vallaeys, Mustafa Shukor, Matthieu Cord, and Jakob Verbeek. Improved baselines for data-efficient perceptual augmentation of llms. arXiv preprint arXiv:2403.13499, 2024.

A Results and Discussion

A.1 LLM-Based Image Data Augmentation

Table 4. List of Multi-modal LLMs in Image Data Augmentation (Preprints)

LLM Name	Augmentation Method	Application and Outcomes	Limitations
Image Augmen-	Utilizes LLMs and diffusion models to generate high-quality,	Demonstrates significant improvements in semantic segmen-	Dependent on the sophisticated integration of LLMs and diffu-
tation Agent	diverse training images for weakly supervised semantic segmen-	tation on PASCAL VOC 2012 and MS COCO 2014 datasets by	sion models, which requires careful calibration and high com-
(IAA) [131]	tation, incorporating a self-refinement mechanism for prompt	enriching training data diversity and quality.	putational resources.
	and image quality control.		
READ [268]	Empowers LLMs to discern 'where to attend' using a novel	Introduces READ to improve reasoning by refining point-based	Relies on detailed similarity maps and may need precise cali-
	architecture, enhancing task-specific model integration through	activations from similarity maps, significantly boosting reason-	bration to ensure effectiveness across varied tasks.
	the innovative use of <seg> tokens in multimodal contexts.</seg>	ing accuracy in visual tasks.	
T2Vid [134]	Explores enhancing video understanding in MLLMs using syn-	Demonstrates efficient fine-tuning techniques with synthetic	Depend heavily on the quality of synthetic data and its align-
	thesized video-like samples for training, reducing reliance on	data to achieve superior performance, even with reduced sample	ment with real video characteristics.
	extensive real video datasets.	sizes.	
LaB-RAG [132]	Introduces Label Boosted Retrieval Augmented Generation	Demonstrates superior performance in both natural language	Critiques commonly used RRG metrics and discusses the po-
	(LaB-RAG), a method combining image-derived labels with	and radiology-specific metrics, surpassing other retrieval-based	tential overvaluation of results, advocating for more accurate
	retrieval-augmented generation to improve radiology report	and some fine-tuned methods.	evaluation methods.
	generation (RRG) without training deep learning models.		
DIAGen [133]	Introduces DIAGen, an approach to semantically diverse im-	Demonstrates that DIAGen enhances semantic diversity and	Discusses the fidelity-diversity tradeoff, using a weighting
	age augmentation using Gaussian noise and class-specific text	improves classification performance, especially for out-of-	mechanism to mitigate the impact of poorly generated sam-
	prompts from LLMs, built on DA-Fusion.	distribution samples.	ples, thus enhancing the quality of the augmented dataset.
T2Vid [134]	Investigates the use of pre-trained image LLMs for video under-	Develops the T2Vid method to synthesize video-like samples to	Highlights the capability of T2Vid to enhance long video under-
	standing, exploring zero-shot inference and fine-tuning meth-	improve instruction diversity in training, achieving comparable	standing without actual long video data, aiming to refine video
	ods.	results with just 15% of the sample size.	LLM training and data curation.
ForgeryGPT	Introduces a novel multimodal LLM, ForgeryGPT, for image	Develops innovative training strategies and architecture en-	Demonstrates superior performance across multiple bench-
[130]	forgery detection and localization, integrating high-order foren-	hancements, such as the Mask-Aware Forgery Extractor for	marks, providing detailed, convincing explanations and sup-
	sics knowledge and explainable AI capabilities.	precise tampering detection and localization.	porting multi-turn dialogue, advancing the field towards robust,
			explainable image forgery analysis.
Visual Editing	Utilizes a distillation approach with data augmentation to im-	Applied to real-time visual editing tasks, enabling effective color	Fixed sequential tool use, overly strict offline metrics, and limi-
GPT 3.5 Turb	prove fine-tuning in low-data regimes by 25%.	grading based on user input. Demonstrates cost and latency	tation to one-hop responses may not fully capture detailed user
[129]		reduction while maintaining high performance.	preferences.
Pedestrian At- tribute Recogni-	Utilizes a Large Language Model augmented framework with	Applied to the MSP60K dataset, achieving new state-of-the-art	Performance still highly dependent on computational resources.
tion [269]	a Vision Transformer backbone to enhance feature extraction and recognition in pedestrian attribute recognition.	performances. The framework is validated across multiple PAR	Limited by the need for extensive training data and the compu-
		benchmark datasets.	tational intensity of the models.
DALL-M: Context-Aware	Employs LLMs to generate synthetic clinical data, enhancing	Demonstrates significant improvements in machine learning	Relies on extensive clinical data for training, with potential
Clinical Data	context awareness in medical diagnostics. Introduces a novel	model performance in medical diagnostics using augmented	computational and ethical challenges due to data sensitivity.
Augmentation	three-phase feature generation process.	features.	
with LLMs			
[136]			
MM-Instruct:	Leveraging existing LLMs to generate diverse visual instruction	Enhances the instruction-following capabilities of LMMs; sig-	Primarily focuses on generating instruction data; may not di-
Generated	data from image captioning datasets.	nificant performance improvements demonstrated with LLaVA-	rectly address other multimodal interactions or complex sce-
Visual Instruc-		Instruct model.	narios.
tions for Large			
Multimodal			
Model Align-			
ment [135]			

A.2 LLM-Based Text Data Augmentation

A.3 LLM-Based Image Data Augmentation

Table 5. List of Multi-modal LLMs in Text Data Augmentation (Preprints)

TIMN	A	And the street of the street	I. The leaders
LLM Name [182]	Augmentation Method Utilizes a chain-of-thought prompting approach with an LLM	Application and Outcomes Significantly enhances the prediction of depression severity	Limitations Dependent on the quality and relevance of initial transcripts
[102]	to generate synthetic summaries and sentiment analyses for		for effective synthetic data generation
	to generate synthetic summaries and sentiment analyses for	while balancing dataset distributions	101 enective synthetic data generation
[-00]	improving depression prediction		
[132]	Uses image descriptors as labels to enhance retrieval augmented	Applied to radiology report generation, LaBRAG achieves supe-	Performance heavily reliant on the quality of image-derived
[170]	generation for radiology report creation	rior results without fine-tuning DL models	labels and categorical accuracy
[178]	Leverages video and textual data to improve AD translation for	Applied to ADT for German, French, Italian, and English, show-	Depends heavily on the quality and synchronization of video
	Swiss languages	ing promising results in multilingual accessibility	data for accurate AD translation
[177]	Prompt-based data augmentation to detect green practices in	Demonstrated effective use of LLM prompts for generating	Limited to Russian language texts; further testing in other lan
	Russian social media	realistic text samples, improving multi-label classification of	guages needed
		ecological texts	
[181]	AIDBench addresses the authorship identification capability	AIDBench shows that LLMs can significantly exceed random	The study is limited to the datasets and methods used, which
	of LLMs, introducing a benchmark with various datasets. It	chance in identifying authorship, revealing new privacy risks.	may not cover all aspects or types of texts, possibly affecting
	includes two methods, one-to-one and one-to-many identifica-	, , , , , , , , , , , , , , , , , , , ,	generalizability.
	tion, with a focus on privacy risks related to anonymous texts		,
	in systems like peer reviews.		
[184]	Fine-tuning with synthetic dialogue data	Improves Arabic NLP performance on benchmarks with fewer	Limited benchmarks for Arabic, overt tokenization issues
. ,	, , , , , , , , , , , , , , , , , , , ,	parameters	,
[270]	Rephrasing EHRs using LLMs	Synthetic pretraining corpora improve language model perfor-	Limited real clinical text, potential LLM hallucinations
	1 8	mance	,,,
271	Schema and script learning in FastRAG	Improves accuracy and efficiency in network data processing	Challenges with complex queries and explicit entity retrieval
[272]	Retrieval-augmented TTA with Audiobox	Enhances zero-shot and few-shot TTA performance	Requires diverse audio retrieval, complex query handling
[273]	Enhanced reference handling with LLM-Ref	Improves reference synthesis and handling in writing tools	Implements direct paragraph retrieval, avoiding chunking and
(=)			indexing issues
I.I.M-	Introduces scaling laws for evaluating LLM-generated text	Proposes data augmentation methods for enhancing text classi-	Uses fuzzy computing to assess data value, aligning it with
Generated	and a second sec	fication	human language standards
NL Meets Scal-			
ing Laws [274]			
AugGPT: Lever-	Utilizes ChatGPT for generating auxiliary samples for few-shot	Demonstrates double-digit improvements in sentence classifi-	Generates diversified and accurate augmented samples, improv
aging ChatGPT	text classification	cation accuracy	ing model performance
for Text Data			0 1
Augmentation			
[179]			
LLMs vs Estab-	Compares LLM-based and traditional text augmentation meth-	Finds LLMs advantageous mainly when using few seeds, with	Suggests traditional methods often perform comparably or bet
lished Methods	ods across multiple datasets and classifiers.	diminishing returns as seed count increases.	ter in terms of cost-effectiveness and accuracy.
[183]	ous across multiple datasets and classifiers.	ummisming returns as seed count mercases.	ter in terms of cost-effectiveness and accuracy.
LLM2LLM	Introduces a novel iterative data enhancement technique using	Focuses on low-data regimes, significantly enhancing LLM per-	Demonstrates substantial performance improvements across
[180]	a teacher LLM to improve student LLM training.	formance by targeting incorrect predictions.	several datasets, reducing the need for extensive data collection.
LLM-based	Introduces a DP-based data augmentation method using LLMs	Employs a knowledge distillation approach for DP-based dis-	Demonstrates significant performance improvements in text
Privacy Data	and a DP-based discriminator for private domain text classifica-	crimination and introduces a DP-based tutor for distribution	classification within private domains while ensuring privacy
Augmentation	tion.	control	protection.
[275]	tion.	control.	protection.
LATEX-GCL	Introduces a novel framework utilizing LLMs for data augmen-	Proposes three types of textual augmentations via LLMs:	Shows superior performance on TAG datasets, effectively over-
[276]	tation in Text-Attributed Graphs (TAGs) for Graph Contrastive	shorten, rewriting, expansion. Uses carefully crafted prompts	coming information loss and semantic deficits, thus setting a
[270]			
	Learning (GCL), addressing limitations of conventional feature	to guide LLMs, enhancing transparency and control over aug-	new standard for GCL applications in TAG settings.
OPT (form)	augmentation and improving semantic richness.	mentation processes.	D III II I
GPT-4 [277]	Improving Real-Time Response in IoT Devices Using Edge Com-	Investigates the impact of integrating edge computing with IoT	Proposes a new architecture that reduces latency and increases
	puting	devices to enhance real-time data processing capabilities.	efficiency, validated through multiple real-world tests.
LLM-based	Random selection of samples for few-shot text augmentation	Explores few-shot sample selection strategies for enhancing	While some informed strategies occasionally improve perfor-
Augmentation		classifier performance in LLM-based text augmentation, assess-	mance, random selection remains comparably effective, sug-
[278]		ing effectiveness on both in-distribution and out-of-distribution	gesting limited benefits from more complex selection methods.
		data	
Curriculum-	Utilizes Curriculum-style Data Augmentation (CDA) to tackle	Applies to metaphor detection to enhance the performance of	Limited by data imbalance and diminishing returns in later
style Augmen-	data scarcity in metaphor detection by incrementally fine-	open-source LLMs, reducing inference costs and improving	iterations, leading to potential declines in model performance
tation [279]	tuning with progressively challenging data	efficiency	over time.
DALDA [122]	Leverages the LLM and Diffusion Model (DM) with Adaptive	Applied to enhance data augmentation in few-shot settings by	Faces challenges with data diversity management, potentially
. ,	Guidance Scaling (AGS) for generating semantically rich syn-	dynamically adjusting the guidance weight based on CLIPScore,	generating less diverse data under constrained guidance set
	thetic images	ensuring target distribution adherence	tings.
[202]	Implements diversity incentives including taboo words, chain-	Applied in paraphrase generation to enhance the lexical diver-	Inconsistent improvements in lexical diversity and mixed results
(202)	ing, and hints in LLM paraphrasing	sity and performance of downstream classification models	on downstream model performance, with only hints method
	пів, ана піно пі сым рагаритазіну	sity and performance of downstream classification models	showing significant positive outcomes.
Innal	Employs LLMs to generate synthetic code-mixed data for senti-	Demonstrates the effectiveness of LLMs in improving senti-	Significant F1 score improvement in Spanish-English; mixed
[280]			
	ment analysis, enhancing model performance	ment analysis in multilingual contexts, particularly in Spanish-	results in Malayalam-English depending on baseline quality.
fac.)	* 1	English setups	F. I. d. FD. I. I. I.
[281]	Implements data augmentation techniques like EDA, Back	Shows that basic data augmentation methods can outperform	Finds that EDA and simple augmentation strategies often yield
	Translation, and LLM-based methods for text classification in	complex LLM techniques in scenarios of data scarcity	better results than LLM-based augmentation in text classifica-
	six Indian languages		tion tasks.
GPT3.5-turbo	Introduces PromptMix, a method that enhances data augmenta-	Demonstrates that PromptMix can effectively improve knowl-	Finds that 2-shot PromptMix outperforms traditional 5-shot
[282]	tion by generating challenging text augmentations near class	edge transfer from large LLMs to smaller models, enhancing	data augmentation methods across multiple datasets, indicating
	boundaries and relabeling them for accuracy	text classification in data-scarce scenarios	its efficiency in leveraging few-shot setups.
GPT-3.5 [283]	Explores the impact of LLM-generated datasets on the distri-	Demonstrates how "in-the-wild" generative data augmentation	Shows that models trained on a mix of real and generated data
(===)	butional robustness of QA models under natural distribution	can enhance domain generalization in QA systems	perform better on naturally shifted distributions compared to
	shifts	Someting Seneralization in Ser of section	those trained solely on real data.
	Introduces LA-TAG, a novel method that leverages LLMs for	Demonstrates superior performance in node classification on	Shows that integrating synthetic text-attributed nodes into
TTM-based			
LLM-based			
Augmen-	text-based data augmentation to address class imbalance in text-	various datasets compared to traditional non-textual data aug-	
Augmen- tation on		various datasets compared to traditional non-textual data aug- mentation strategies	graphs significantly reduces the performance gap between mi nority and majority nodes.
Augmen- tation on Text-Attributed	text-based data augmentation to address class imbalance in text-		
Augmen- tation on	text-based data augmentation to address class imbalance in text-		graphs significantly reduces the performance gap between minority and majority nodes.

Table 6. List of Multi-modal LLMs in Speech Data Augmentation (Preprints)

LLM Name	Augmentation Method	Application and Outcomes	Limitations
AudioSetMix [207]	LLM-assisted augmentation for audio-language datasets	Enhanced performance on audio-language benchmarks by di- versifying training examples and addressing data set limitations.	Relies heavily on the alignment and quality of LLM-genera
Synthio [208]	Enhances small-scale audio classification datasets with syn- thetic data via text-to-audio models	Improves classification accuracy by generating acoustically con- sistent and compositionally diverse synthetic audio data	Depends on the alignment of synthetic audio with actual dataset characteristics for effective augmentation
LLM-powered	Leverages LLMs to enhance data for multilingual commonsense	Demonstrates that LLM-generated data can effectively improve	Highlights challenges in generating coherent data in some lan-
Data Augmen-			
tation [187]	reasoning tasks	the performance of multilingual models on limited datasets	guages like Tamil; shows LLMs' uneven performance across different languages
Text-to-Audio	Introduces the TANGO model, leveraging instruction-tuned	Highlights the integration of FLAN-T5 for enhanced text com-	Demonstrates improved model performance through innovative
Generation	LLMs for effective text-to-audio generation, significantly out-	prehension and audio generation, with specific focus on main-	audio mixing techniques based on audio pressure levels
[285]	performing previous models on a smaller dataset	taining model diversity without fine-tuning during training	
Audio Dia-	Introduces a novel dataset for enhancing audio and music un-	Utilizes a unique prompting-based approach with existing	Provides an extensive evaluation of the dataset's utility, demon-
logues [221]	derstanding through multi-turn dialogues, consisting of over	datasets to create dialogues that explore the subtleties of audio	strating its potential to significantly advance the field of audio
	163,000 samples, aimed at training models to handle complex	events, enabling deeper model training on enhanced audio fea-	interaction models.
	interactive tasks in audio analysis.	tures.	
UniAudio [222]	Introduces a universal audio generation model capable of han-	Utilizes innovative LLM techniques for effective tokenization	Demonstrates superior performance across various audio tasks,
	dling multiple audio tasks including speech, sound, music, and singing synthesis with a single model architecture.	and sequence prediction, enhancing the model's ability to handle complex audio generation tasks efficiently.	supported by extensive training on diverse datasets, showcasing its adaptability and potential as a foundational model for future audio applications.
Augment, Drop	Introduces Augmented View Dropout and TextSwap techniques	Applied to music-text representation learning, demonstrating	Does not address potential biases or inconsistencies introduced
and Swap [286]	for diversifying text inputs in music-text contrastive learning	significant improvements in model robustness and retrieval accuracy without additional computational costs	by synthetic text augmentation and relies on the quality of initial tag annotations for effective training
DiveSound	Employs LLMs to automatically construct a taxonomy for di-	Enhances audio diversity in generation tasks by utilizing a	The framework's effectiveness can be limited by the accuracy
[287]	verse audio generation, integrating multimodal data.	new dataset with diverse subcategories informed by visual and	of the LLMs in generating coherent and relevant subcategories
		textual data, improving sound quality and diversity.	and the alignment of multimodal data.
Audio-Agent	Utilizes a pre-trained TTA diffusion model and GPT-4 for de-	Provides high-quality audio generation aligned with complex	The method's dependency on the quality of LLM decomposi-
[223]	composing text into specific instructions for audio generation;	textual or video inputs, supporting variable-length and multi-	tions and the accuracy of semantic and temporal alignments
	employs Gemma2-2B-it for bridging video and audio modalities with temporal alignment.	modal audio generation tasks.	might limit its application in more dynamic or unpredictable scenarios.
Audio-Visual	Integrates modality-specific tokens to activate visual or au-	Demonstrates strong zero-shot performance on diverse video	May be constrained by the reliance on accurate modality-
LLM [288]	ditory encoders for holistic video understanding; includes a high-quality video instruction dataset from GPT-4.	understanding tasks like MSRVTT-QA, significantly surpassing non-LLM methods.	specific token activation and the dataset's quality for training effectiveness.
Audio-Visual	Integrates modality-specific tokens to activate visual or au-	Demonstrates strong zero-shot performance on diverse video	May be constrained by the reliance on accurate modality-
LLM [288]	ditory encoders for holistic video understanding; includes a high-quality video instruction dataset from GPT-4.	understanding tasks like MSRVTT-QA, significantly surpassing non-LLM methods.	specific token activation and the dataset's quality for training effectiveness.
Contextual ASR [220]	Uses contextual cues to enhance ASR accuracy	Significant reduction in word and entity error rates in ASR systems	Relies heavily on precise initial entity recognition
Make-An- Audio 2 [289]	Employs structured text parsing and temporal alignment for audio synthesis	Improved alignment and audio quality; surpasses existing mod- els	Dependent on the precision of initial text parsing
AudioBERT	Enhances BERT by injecting auditory knowledge	Integrates auditory commonsense into BERT, enhancing model	Requires accurate detection of auditory knowledge spans
[290]		performance	
Codecfake [291]	Utilizes neural codecs for waveform manipulation in deepfake detection	Efficiently detects deepfake audios by reducing equal error rate	Struggles to detect without traditional vocoder artifacts
SpeechVerse	Merges speech and text foundation models for robust multi-task	Outperforms traditional models in diverse speech processing	Needs further adjustments for consistent performance across
[292]	training	tasks	tasks
Enhancing	Focuses on temporal reasoning in audio QA through curriculum	Introduces effective strategies and a novel metric, improving	Performance gain without losing capabilities in other areas
Temporal Un-	learning	temporal reasoning	
derstanding			
in AQA for			
LALMs [219]			
Improved Base-	Studies interfacing mechanisms between LLMs and perceptual	Introduces DePALM, enhancing performance with reduced	Demonstrates advancements in LLM interface techniques in
lines for Data- efficient Percep-	backbones	training time	low-data settings
tual Augmenta-			
tion of LLMs [293]			