1. Introduction

In an increasingly digital world, where the exchange of information happens at an unprecedented pace, understanding human emotions from written text has become a paramount challenge. Our project, titled "Real-time Emotion Recognition from Text Using Deep Learning," aims to revolutionise how we decipher and utilise the underlying emotions within the vast sea of textual data that engulfs us daily. In a world where sentiment analysis, customer feedback interpretation, and social media monitoring have profound implications for businesses and society at large, our project emerges as a pioneering endeavour that seeks to enhance our capacity to comprehend and respond to the intricacies of human emotions.

The essence of this project lies in its commitment to real-time emotion analysis, offering the promise of instantaneous insight into the emotional content of textual data. With this capability, organisations can respond swiftly to customer feedback, identify emerging trends in social media discourse, and craft more personalised and empathetic responses. Moreover, our project is not bound by linguistic constraints; it transcends language barriers, enabling emotion recognition across a multitude of languages, thereby fostering global connectivity and understanding.

Central to the success of our project is the implementation of cutting-edge deep learning techniques, which have demonstrated remarkable performance in various natural language processing (NLP) tasks and hold the key to achieving high accuracy in emotion detection. Additionally, our project relies on the versatility of Python as the primary programming language, known for its robust ecosystem of libraries and frameworks conducive to the development of sophisticated machine learning systems. To bring our real-time emotion recognition system to life, we will leverage web frameworks for creating a user-friendly, interactive, and dynamic web application that allows users to engage with the technology effortlessly.

The journey we embark upon is not only technologically exhilarating but also socially transformative. As we delve into the realm of emotions hidden within the written word, we open new avenues for enhancing communication, decision-making, and user experiences across diverse domains. With the potential to revolutionise how we understand and respond to human emotions in real-time, our project represents a pivotal step forward in the ever-evolving landscape of artificial intelligence, natural language processing, and human-computer interaction. Our project aims to bridge the gap between the abundant organisations and the emotional communication of users, which helps in better emotional understanding of the users and benefits the organisations for analysis tasks.

2. Defining the Scope:

The scope of our project, "Real-time Emotion Recognition from Text Using Deep Learning," encompasses the development of an advanced system capable of instantaneously detecting emotions expressed in written text. This project aims to address the growing demand for efficient sentiment analysis, customer feedback assessment, and social media monitoring tools.

The primary objective of this is to introduce a novel system and method for utilising deep learning to accurately detect emotions in text. This model arises from the need to accurately decipher emotions in digital text. Traditional methods fall short in capturing the complexity of human sentiment expressed online. This invention recognizes the potential of deep learning, especially neural networks, to revolutionise emotion analysis by leveraging their success in various domains.

The surge in digital communication emphasises the demand for automated tools to process vast amounts of textual data swiftly and meaningfully. The model's foundation lies in combining deep learning's capabilities with the growing importance of artificial intelligence and natural language processing, enabling accurate emotion detection and valuable feedback provision. This addresses challenges in understanding emotions, enhancing decision-making, and improving various aspects of digital interaction. Key features include real-time emotion analysis, high accuracy, and scalability to handle a substantial volume of concurrent text inputs.

Our project's primary focus is on leveraging Natural Language Processing (NLP) techniques, including tokenization, text preprocessing, and feature extraction. Deep Learning models, such as Recurrent neural networks (RNNs), Convolutional Neural Networks (CNNs), or Transformer-based architectures, will be fine-tuned to achieve high accuracy in emotion detection across a broad spectrum of emotions. To make our system user-friendly and accessible, we will develop a real-time web application using Python and a suitable web framework. This web application will allow users to interact with the system, input text data, and receive instantaneous emotion predictions.

Ultimately, our project aims to provide a valuable and versatile tool for businesses and researchers seeking to gain insights from textual data across various domains and languages

3. Search Strategy

Our approach to conducting this literature survey for our project, "Real-time Emotion Recognition from Text Using Deep Learning," comprises two distinct stages, each involving several critical activities that collectively contribute to building a comprehensive knowledge base for our research.

In the first stage, our primary focus is on gathering relevant information related to our project's topic. This stage encompasses several key activities:

We begin by meticulously identifying a set of search terms that are directly related to our research area. These search terms include phrases such as "emotion recognition" "deep learning" "NLP" "real-time processing.". These terms are instrumental in guiding our search for pertinent literature.

We have judiciously chosen three renowned academic publishers' databases, namely IEEE, ScienceDirect, and Springer. These databases are well-regarded for hosting peer-reviewed research articles in fields relevant to our project, including Natural Language Processing, Artificial Intelligence, and Human-Computer Interaction.

In addition to the primary databases, we've also conducted supplementary searches on arXiv, Google Scholar, and JSTOR. These platforms have provided a substantial volume of publications and research material pertinent to our project's goals.

The second stage of our study entails an in-depth analysis of the retrieved articles. This stage is vital for organising and categorising the literature, ensuring its relevance to our research objectives.

Our initial search returned a considerable volume of research articles spanning several decades. To manage this extensive dataset, we employ a systematic filtering process. We focus on articles published in the recent decade, as this timeframe aligns with the peak of research publication on our topic, as revealed through the analysis of Scopus database records.

In the subsequent step, we apply further filtering by assessing the titles of the articles. This step is pivotal for narrowing down our selection to only the most relevant pieces of literature. Additionally, we consider publications that offer comprehensive literature reviews and surveys of emotion recognition to gain insights into the state of the art and the field's evolution.

To maintain the focus of our study on Deep Learning algorithms and Natural Language Our article selection process includes combining articles obtained from various sources, including journal databases and arXiv.

As a final step, we delve into the bibliographies of selected articles to identify additional sources that may be pertinent to our research. This comprehensive approach extends to using Google Scholar to retrieve full-text copies of potential articles referenced in the bibliographies.

4. Selection Criteria:

In our quest to select the best sources on emotion recognition in text, we adhere to a rigorous set of selection criteria, ensuring that the chosen materials are not only comprehensive but also reflect diverse methodologies, techniques, and algorithms relevant to the field. Here's how we have executed this selection process:

4.1. Focus on Relevance:

In our search for sources, we prioritise relevance to the domain of emotion recognition in text. We have specifically focused on materials that directly address or contribute substantially to the understanding and advancement of emotion recognition techniques in textual data.

Example: We have identified sources that delve into the application of deep learning models, such as LSTM (Long Short-Term Memory) networks, for emotion recognition in text, as this aligns with our project's technological framework.

4.2. Credible Source Selection:

Credibility is a cornerstone of our selection process. We have taken great care to select sources from reputable publishers, established journals, renowned conferences, and reputable institutions. These sources undergo rigorous peer review, ensuring their reliability.

Example: We have considered papers published in the International Journal of Artificial Intelligence Research and IEEE publications as it is a well-regarded paper searching sources in the field of AI and NLP.

4.3. Interdisciplinary Inquiry:

Recognizing the multidisciplinary nature of emotion recognition in text, we have actively sought sources that offer insights from various disciplines, such as Natural Language Processing (NLP), Machine Learning, and Psychology.

4.4. Emphasised Methodological Rigour:

We have placed a premium on sources that demonstrate strong methodological rigor. This includes sources that outline clear experimental methodologies, comprehensive data preprocessing techniques, and robust evaluation procedures for emotion recognition algorithms.

Example: We have incorporated research papers that thoroughly explain the use of deep neural networks, including Recurrent neural networks (RNNs), CNNs (Convolutional Neural Networks), for sentiment analysis in social media data. The paper's rigorous methodology enhances its reliability.

4.5. Prioritised Real-World Applicability:

To ensure the practical relevance of our selected sources, we have favoured materials that discuss the real-world applications of emotion recognition techniques, particularly in areas like customer sentiment analysis, mental health monitoring, and chatbot interactions. Like we have included case studies from leading technology companies showcasing the implementation of emotion recognition algorithms in their customer feedback analysis systems.

4.6. Novelty Assessment:

We prioritise sources that contribute fresh insights, innovative approaches, or novel applications to the field of emotion recognition in text. Novelty ensures that the selected sources bring unique perspectives and advancements to our research.

4.7. Cross-Domain Relevance:

We favour materials that transcend specific domains and offer valuable insights applicable across a range of industries and contexts. Such sources enrich our understanding by providing versatile applications of emotion recognition techniques.

4.8. Promoted Diversity of Algorithms and Techniques:

Our selection strategy has ensured diversity in terms of the algorithms and techniques discussed in the sources. This encompasses various deep learning architectures, feature extraction methods, and sentiment lexicons, fostering a well-rounded understanding of the field.

4.9. Open-Source Availability:

Open-source availability is an essential criterion in our selection process. We give preference to sources that not only describe innovative methods but also make their code, models, or datasets openly accessible. Open-source resources facilitate reproducibility and further research in the community.

Example: We included survey articles that comprehensively reviews a spectrum of sentiment analysis techniques, including rule-based methods, machine learning approaches, and deep learning models like Transformers.

By adhering to these selection criteria, we have meticulously curated a collection of sources that collectively offer a rich and varied perspective on emotion recognition in text. These sources encompass a wide array of methodologies, techniques, and algorithms, thereby enriching our project with a comprehensive knowledge base from which to draw insights and inspiration.

5. Data Extraction

By analysing the research papers related to the project on "Real-time Emotion Recognition from Text Using Deep Learning," here are some key findings you might have discovered:

5.1.Key Findings:

1. State-of-the-Art Models:

We identified the most advanced deep learning models and techniques for real-time emotion recognition from text, such as Transformer-based models or hybrid architectures.

2. Accuracy and Performance:

Our analysis made us have the accuracy and performance levels of few achievable models and approaches in the field.

3. Scalability:

We have identified models or techniques that are scalable for processing a large volume of text inputs concurrently, a crucial factor for real-time applications.

4. Ethical Considerations:

Our research highlights ethical considerations related to bias, fairness, and privacy in emotion recognition systems, as discussed in the literature.

5. Real-World Applications:

Key findings may include insights into practical applications of real-time emotion recognition, such as sentiment analysis in customer feedback or social media monitoring.

6. Challenges and Open Questions:

Your analysis could reveal challenges that remain in the field, such as cross-cultural emotion recognition, subtle emotion detection, or addressing bias and fairness issues.

7. Datasets and Resources:

Key findings might include the availability of datasets, pre-trained models, and resources for building emotion recognition systems.

8. Future Directions:

Based on your review, you could suggest potential future directions for research in real-time emotion recognition, identifying areas where further investigation is needed.

5.2. Methodologies:

In the field of emotion recognition from text, various approaches, methodologies, and algorithms have been developed to analyse and classify emotions expressed in textual data. Here are different categories of approaches and some examples of algorithms/methodologies within each category:

1. Lexicon-Based Approaches:

- Lexicon-based methods rely on emotion lexicons or dictionaries containing words and their associated emotions. They calculate emotion scores based on the presence of specific emotion-indicative words.
- EmoLex: A lexicon-based approach that assigns emotion labels (e.g., joy, sadness) to words in the text based on predefined lexicons.
- SentiWordNet: An extension of WordNet that assigns sentiment scores to words, which can be used for emotion analysis.

2. Machine Learning Approaches:

- Machine learning methods involve training models to recognize emotions based on labelled training data. These models can include both traditional machine learning algorithms and deep learning models.
- Naive Bayes Classifier: A probabilistic model that can be used for sentiment and emotion classification.
- Support Vector Machines (SVM): A supervised learning method that can classify text data into emotional categories.

3. Deep Learning Approaches:

- Convolutional Neural Networks (CNNs):

  Convolutional Neural Networks (CNNs) are deep learning models originally designed for computer vision tasks but have also found applications in natural language processing, including text classification. CNNs are particularly effective at capturing local patterns in data. In the context of text classification, these local patterns often refer to sequences of words or phrases that convey meaningful information about the emotions expressed in the text.

  CNNs employ convolutional layers that apply a set of learnable filters or kernels to small portions of the input data. These filters slide across the text data, convolving it and extracting features. The extracted features can represent various aspects of the text, such as word combinations, n-grams, or specific syntactic structures.

  For emotion analysis, CNNs can identify relevant patterns in text, such as the presence of emotive words or phrases, punctuation, and sentence structure. These patterns contribute to the model's ability to classify text into different emotion categories.

- Recurrent Neural Networks (RNNs):

  Recurrent Neural Networks (RNNs) are a class of deep learning models that excel in capturing sequential dependencies in data, making them well-suited for processing text, which is inherently sequential. In the context of emotion analysis, RNNs can capture the order in which words or phrases appear in a sentence, as well as the dependencies between them.

  RNNs maintain a hidden state that evolves as each word or token in the input sequence is processed. This hidden state serves as a memory of the previous tokens seen in the sequence, allowing the model to contextualise the current token based on what it has seen before. This makes RNNs effective at understanding the sequential nature of text data and identifying patterns related to emotions.

- Long Short-Term Memory (LSTM):

  Long Short-Term Memory (LSTM) is a specialised variant of RNNs designed to overcome the vanishing gradient problem and capture long-range dependencies in sequences. Emotion analysis often requires understanding nuanced emotions expressed in lengthy text passages, and LSTMs are well-suited for this task.

  LSTMs incorporate a gating mechanism that allows them to retain information over long sequences while preventing the vanishing gradient problem that standard RNNs face. This makes LSTMs effective at capturing the context of text data and recognizing complex emotional expressions that span multiple sentences or paragraphs.

In the context of emotion recognition, LSTMs can discern subtle shifts in emotion, track emotional arcs in narratives, and provide context-aware predictions based on the entire text input.

- Bidirectional Transformers (BERT):

  Bidirectional Transformers, commonly represented by models like BERT (Bidirectional Encoder Representations from Transformers), have revolutionised natural language processing tasks, including emotion analysis. These models are pre-trained on massive text corpora and are capable of understanding contextual relationships between words in both directions (left-to-right and right-to-left) within a sentence.

  BERT-based models have the ability to capture complex contextual information and have shown remarkable performance in various NLP tasks. For emotion analysis, BERT-based models can comprehend the nuances of emotional expressions by considering the entire context in which words or phrases appear. This context-awareness enables BERT to excel in recognizing emotions in text, especially in cases where subtle emotional cues are scattered throughout longer text passages.

- Gated Recurrent Units (GRUs):

  Gated Recurrent Units (GRUs) are another variant of RNNs designed to capture sequential dependencies while addressing some of the issues associated with vanishing gradients. GRUs are computationally efficient and have become popular choices for NLP tasks, including emotion analysis.

  GRUs utilise gating mechanisms similar to LSTMs but with a simplified architecture. This simplicity makes them easier to train and faster to converge. GRUs are effective at capturing dependencies in sequential data, which is crucial for understanding emotional expressions that unfold over the course of a text.

4. Ensemble Approaches:

- Ensemble methods combine predictions from multiple models to enhance accuracy and robustness in emotion recognition.
- Random Forest: An ensemble learning method that combines predictions from multiple decision trees.
- Voting Classifier: Combines predictions from multiple classifiers to make a final prediction.

5. Hybrid Approaches:

- Hybrid methods combine lexicon-based and machine learning or deep learning techniques to leverage the strengths of both approaches.
- Lexicon-Enhanced Deep Learning: Incorporates lexicon-based features into deep learning models to improve performance.

6. Rule-Based Approaches:

- Rule-based systems use predefined linguistic rules to detect emotions based on syntactic and semantic patterns in text.
- Pattern-Based Rules: Specify patterns or rules for identifying emotional expressions in text.

7. Multi-Modal Approaches:

- Multi-modal methods combine text with other modalities, such as images, audio, or physiological signals, to improve emotion recognition accuracy.
- Audio-Text Fusion: Combines audio and text data to analyse emotions in multimedia content.

5.3. WorkFlow

a. Input Text Data via Web Interface:

The process commences with users interacting with a web interface specifically designed for text input. Users can enter raw textual content into input fields provided by the web application.

This textual input can be sourced from various channels, including customer reviews, social media comments, or any text-based source that users wish to analyse for emotions.

In the context of our web-based emotion recognition system, the user's input through the web interface becomes the text data to be processed and analysed.

b. Preprocessing:

Raw textual data often contains noise and inconsistencies. Preprocessing is essential to clean and structure the text for further analysis.

- Tokenization: The text is divided into individual words or phrases (tokens). Tokenization helps break down the text into manageable units for analysis.

- Removal of Punctuation: Punctuation marks, symbols, and special characters are typically removed because they don't carry semantic meaning for emotion recognition.
- Handling of Stop Words: Common words like "and," "the," "is," etc., known as stop words, are often removed as they are less informative for emotion analysis.
- Lowercasing: Text is often converted to lowercase to ensure uniformity.

c. Text Embedding:

Once the text is preprocessed, it needs to be transformed into numerical vectors that can be fed into a deep learning model.

Text embedding techniques, such as Word2Vec, GloVe, or pre-trained language models like BERT or GPT, are used for this purpose.

These embeddings capture the semantic meaning of words and phrases, creating vector representations that retain the relationships between words.

d. Deep Learning Model:

The core of the system is a deep learning architecture, which can be one of several types, depending on the specific use case and data.

Recurrent Neural Networks (RNNs): These are capable of handling sequential data and are commonly used for text-based emotion recognition. Long Short-Term Memory (LSTM) networks are a popular choice within RNNs.

Transformer-Based Models: Transformers, like BERT or GPT, have achieved remarkable results in various NLP tasks, including emotion recognition. They are known for their attention mechanisms that can capture context effectively.

e. Emotion Classification:

The primary task of the deep learning model is to classify the text into different emotion categories. These categories can include happiness, sadness, anger, surprise, and more, depending on the specific emotions you aim to recognize.

The model learns from labelled training data, where texts are associated with emotion labels. Through training, the model generalises its understanding of how different emotions are expressed in text.

During training, the model adjusts its internal parameters (weights and biases) to minimise the difference between its predictions and the true emotion labels.

f. Detected Emotion:

The output of the emotion classification stage is the detected emotion label associated with the input text.

This label represents the primary emotion conveyed within the text. For example, if the model classifies a customer review as "joy," it indicates that the primary emotion expressed in the review is happiness or satisfaction.

In summary, the process involves preprocessing the input text, transforming it into numerical vectors, feeding it into a deep learning model for emotion classification, and obtaining the detected emotion label as the output. This allows you to analyse and understand the emotional content of text data, which can be valuable in various applications, such as sentiment analysis, customer feedback analysis, and more.

6. Identifying Gaps

Identifying gaps in the existing literature is essential for shaping the direction of your research on real-time emotion recognition from text using deep learning. Here are some areas where further research may be needed or where the current research may be insufficient:

1. Emotion Detection in Low-Resource Languages:
- Much of the existing literature focuses on emotion recognition in major languages. There is a need for research in low-resource languages to make the technology more inclusive.

2. Cross-Cultural Emotion Recognition:
- Emotions can be expressed differently across cultures, which poses a challenge for current models. Research on cross-cultural emotion recognition is essential for global applications.

3. Long-Context Emotion Recognition:
- While current models perform well on short texts, such as tweets or short comments, there is a gap in recognizing emotions in longer texts, such as articles or essays, where context may evolve.

4. Emotion Evolution Over Time:
- Emotions in text may change over time, especially in dynamic platforms like social media. Research into modelling the temporal aspect of emotions is needed for real-time analysis.

5. Real-time Processing Efficiency:
- Despite advancements, achieving real-time processing efficiency without compromising accuracy remains a challenge. Further research is needed to optimise deep learning models for faster predictions.

6. Ethical Considerations and Bias Mitigation:
- There is a gap in understanding and addressing potential biases in emotion recognition models, especially when dealing with diverse and user-generated text data. Research on fair and unbiased models is crucial.

7. Multimodal Emotion Recognition:
- Many real-world scenarios involve both text and other modalities (e.g., images, audio). Research on multimodal emotion recognition, where multiple data sources are combined, is lacking.

8. Transfer Learning and Few-shot Learning:
- Research into transfer learning and few-shot learning techniques can enable emotion recognition models to adapt quickly to new domains or languages with limited training data.

9. Emotion Detection in Non-Standard Text:
- Current models are often trained on standard text genres. More research is needed to recognize emotions in unconventional text types, such as code, legal documents, or medical records.

10. User Feedback Integration:
- While user feedback can be valuable for model improvement, there is a gap in how to effectively integrate such feedback into the real-time emotion recognition process.

11. Robustness to Slang and Informal Language:
- Many text inputs, particularly on social media, contain slang and informal language. Models need to become more robust in understanding and recognizing emotions in such contexts.

12. Real-time System Evaluations:
- Existing literature often lacks comprehensive evaluations of real-time emotion recognition systems in practical, real-world settings. More studies on system performance and user satisfaction are needed.

Identifying these gaps and areas for further research can guide your project to contribute to the advancement of real-time emotion recognition, ensuring that our work addresses critical challenges and adds value to the existing literature.

7. Discussion:

The discussion of the implications of findings from the literature review is a crucial aspect of any research project, as it sheds light on the existing body of knowledge and its relevance to the specific research question. In this case, we are examining the literature related to "Real-time Emotion Recognition from Text Using Deep Learning." This discussion will delve into the significance of the identified research and its contributions to the broader field of emotion recognition, NLP, and deep learning.

One of the primary implications drawn from the literature review is the growing importance of emotion recognition in various applications. Emotion recognition has evolved from being merely a component of sentiment analysis to a field with vast implications for human-computer interaction, mental health monitoring, customer feedback analysis, and more. The literature highlights how advancements in deep learning techniques, such as Convolutional Neural Networks (CNNs) and Transformers, have significantly improved the accuracy and reliability of emotion recognition systems. This suggests that the field has reached a level of maturity where real-time emotion recognition from text is not only feasible but also increasingly accurate and relevant.

The significance of the existing research in relation to the research question of real-time emotion recognition is noteworthy. The literature review has revealed that researchers have made substantial progress in developing models and algorithms capable of processing text inputs and providing instantaneous emotion predictions. This aligns with the core objective of the project, which is to build a real-time emotion recognition system. The findings of the literature review serve as validation that this research question is not only relevant but also timely in the context of recent advancements in deep learning and NLP.

Furthermore, the literature review showcases the versatility and adaptability of deep learning models, such as Transformers like BERT, in the context of emotion recognition. These models, originally designed for natural language understanding tasks, have been fine-tuned to excel in recognizing emotions from text. This adaptation underscores the interconnectedness of various subfields within machine learning and artificial intelligence. It suggests that the advancements made in one domain can have ripple effects across others, leading to innovative solutions to longstanding problems. In this case, the fusion of NLP and deep learning has led to breakthroughs in emotion recognition, which can be applied in real-time scenarios.

The broader field of emotion recognition and NLP also benefits from the findings of the literature review. The ability to accurately detect and understand emotions in text has implications far beyond the scope of this project. It can enhance human-computer interaction by enabling systems to respond empathetically to user inputs, whether in chatbots, virtual assistants, or educational platforms. It can revolutionise mental health monitoring by automating the analysis of text data to detect signs of emotional distress or changes in mood.

It can assist businesses in analysing customer feedback and social media sentiment in real time, helping them make data-driven decisions and respond to customer needs promptly.

Moreover, the literature review reveals the importance of multi-language support in emotion recognition. The ability to recognize emotions across various languages is a valuable asset in an increasingly globalised world. It enables cross-cultural analysis, facilitates international customer feedback analysis, and makes emotion recognition tools accessible to a broader range of users. This emphasis on language diversity underscores the need for inclusivity and the adaptation of emotion recognition models to diverse linguistic and cultural contexts.

The literature also highlights the significance of high accuracy in emotion detection. Accuracy is paramount in applications where decisions are based on emotion recognition, such as in mental health assessments or customer sentiment analysis. High accuracy not only ensures the reliability of the system but also minimises the potential for misclassification and its associated consequences. The pursuit of accuracy has led researchers to fine-tune models and develop sophisticated techniques for emotion recognition, contributing to the robustness of the field.

Scalability is another crucial implication discussed in the literature. Real-time emotion recognition systems need to handle large volumes of text inputs concurrently, especially in applications involving social media monitoring or customer support. The literature review demonstrates that researchers have recognized the importance of scalability and have explored various techniques, including distributed computing and efficient model architectures, to address this challenge. Scalability is vital not only for the project at hand but also for its potential to impact large-scale applications across industries.

11. Conclusion

In conclusion, our extensive literature review on "Emotion Detection from Text Using Deep Learning" has provided a comprehensive overview of the current state of research in this dynamic field. Through a systematic search strategy, we collected a wealth of knowledge encompassing a wide range of topics, methodologies, and applications.

We began by defining the scope and importance of emotion detection from text, highlighting its significance in various domains, from sentiment analysis to customer feedback analysis. Our search strategy involved meticulously selecting databases, keywords, and inclusion criteria to ensure a thorough review of the literature.

Our selection criteria and data extraction process facilitated the identification and organisation of pertinent research findings. We synthesised key insights, showcasing the diversity of deep learning approaches, models, and techniques applied to emotion recognition tasks. We also identified gaps in the existing literature, underscoring the need for further research in cross-cultural recognition, real-time processing efficiency, and ethical considerations.

The critical evaluation section shed light on the strengths and limitations of current methodologies, emphasising the importance of addressing bias and privacy concerns in real-world applications. Our discussion delved into the nuances of deep learning models, offering insights into their performance and theoretical underpinnings.

In summary, this literature review has provided a strong foundation for our project on real-time emotion recognition from text using deep learning. It informs our research direction, ensuring that our work builds upon existing knowledge and addresses critical gaps in the field.