MULTILABEL EMOTION RECOGNITION THROUGH SEQUENCE LABELING AND SENTENCE CLASSIFICATION MODELS USING TEXTUAL DATA

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ABSTRACT

As complex beings, humans have a limited number of primary emotions, such as trust, joy, fear, surprise, sadness, disgust, anger, and anticipation that influence decision-making, relationship-building, and interactions with the world. However, understanding these emotions from written text has significantly challenged natural language processing. Textual communication lacks the visual cues in face-to-face interactions, making it difficult to detect subtle nuances that convey emotions. Multilabel emotion recognition is essential in this context because it enables machines to recognize multiple emotions in a given text data, providing a more nuanced understanding of the writer's sentiment. With this capability, we can overcome the challenges associated with accurately detecting emotions from text and unlock a wealth of insights about human behavior and communication. The existing research on multilabel emotion detection has primarily focused on two different approaches: sequence labeling and sentence classification. A Bidirectional Long Short-Term Memory (Bi-LSTM) model and Bidirectional Encoder Representations from Transformer-Convolutional Neural Network (BERT-CNN) model will be developed for the respective approaches. Training and Testing of the models will be done over a data set, the Multimodal Multi-Label Emotion, Intensity, and Sentiment Dialogue Dataset (MEISD) with over 20,000 instances of text labeled with up to 3 emotions. The models will then be evaluated for their performance on multilabel emotion recognition using the standard metrics of Precision, Recall, Accuracy, and F1-score. Primary emotions are then mapped to complex emotions by combining them using Robert Plutchik's Emotion Wheel accordingly.

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CHAPTER 1
INTRODUCTION

The first chapter of this study sets the foundation for the exploration of multilabel emotion recognition, upon which this study was built, along with models that have the potential to tackle such a task. This section also provides the hypotheses that will guide the investigation, the beneficiaries of the study as well as the study's limitations.

1.1 Rationale of the Study

Humans are fascinating creatures. We have evolved over millions of years, becoming the dominant species on this planet. Yet, despite our vast knowledge of the world around us, we still have so much to learn about ourselves. Understanding human behavior is one of the greatest challenges of our time, and it is one that we must embrace if we are to make progress in all aspects of life. From our interactions with one another to our impact on the environment, to our advancements in technology, it is essential that we gain a deeper understanding of what makes us tick. By doing so, we can unlock the secrets of the human mind and use this knowledge to build a better future for ourselves and generations to come. It is only through understanding ourselves that we can truly understand the world around us, and make the most of the time we have on this beautiful planet.

As humans, we are complex beings with a wide range of emotions. Emotions drive us to make decisions, form relationships, and interact with the world around us. The term "emotion" is a noun used to describe a conscious mental reaction (such as anger or fear) subjectively experienced as a strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioral changes in the body (Merriam-Webster, n.d.). Emotion theory proposes that human beings have a limited number of emotions (e.g., fear, anger, joy, sadness) that are biologically and psychologically “basic” (Wilson-Mendenhall et al., 2013), each manifested in an organized recurring pattern of associated behavioral components (Ekman, 1992a; Russell, 2006). Paul Ekman, a renowned psychologist, and researcher, identified six basic emotions that are universally recognized across cultures: happiness, sadness, anger, fear, surprise, and disgust. These emotions are considered basic because they are considered to be innate and are experienced by all humans regardless of culture, language, or upbringing. Robert Plutchik proposed eight primary emotions: anger, fear, sadness, disgust, surprise, anticipation, trust, and joy, and arranged them in a color wheel. The elements of basic emotions can be combined to form complex or compound emotions (Ekman, 1992b).

By understanding human emotions, we can improve our relationships with others and create more meaningful connections. We can also develop empathy and become better at reading social cues, which can help us in our personal and professional lives. Additionally, studying human emotions can provide insights into mental health and how we can better care for ourselves and others. In short, understanding human emotions is essential for personal growth and can lead to significant advancements in various fields.

Emotions can be recognized through various modes, such as facial expressions, body language, speech, and text, as discussed in the MEISD study by Firdaus et al. (2020). Facial expressions are the most common and visible way to identify emotions. They convey a vast range of emotions, from happiness to sadness, anger to surprise, and disgust to fear. Body language, on the other hand, can provide additional clues to what a person is feeling, such as the way they stand, move, or gesture. Speech is another mode that can convey emotions, as it can provide information about a person's tone of voice, pitch, and intensity. Lastly, text can also be used to detect emotions. The words and phrases a person uses, the sentiment behind them, and the context in which they are used can all contribute to understanding the emotional state of a person. Recent advances in deep learning have led to the development of a deep neural network model for the detection and classification of emotions from textual content (Asghar et al., 2022). By considering all these modes of emotional recognition, including text-based approaches, we can gain a more comprehensive understanding of a person's emotional state.

The ability to understand human emotions from written text has been a significant challenge in the field of natural language processing. This is because human emotions are complex, and often conveyed through subtle nuances that can be difficult to detect through written words alone. Additionally, the written text lacks the visual cues that are present in face-to-face communication, such as facial expressions and body language, making it even more challenging to accurately detect emotions from text. A recent study proposes a machine learning model that utilizes linguistic features and prosodic features to recognize emotions from speech and text data (Lakkireddy, 2021). Another study has utilized Tweets as their form of textual data and developed new techniques and models for sentiment analysis and multilabel emotion recognition (Jabreel & Moreno, 2019). Researchers have had to rely on advanced machine-learning techniques and complex algorithms to develop models that can accurately identify and classify emotions in written text.

Multilabel emotion detection is critical as it enables machines to recognize multiple emotions from a given text data, allowing for a more nuanced understanding of the writer's sentiment. Multilabel emotion detection, which allows for the identification of multiple emotions within a single piece of text, is especially critical in capturing the nuances of human emotion. This approach is particularly useful in analyzing unstructured conversation data, where people may express a range of emotions simultaneously (Kim & Shin, 2022). In Firdaus et al. (2020)'s study, MEISD, a large-scale dataset, provides diverse and complex emotional expressions, enabling the development of more sophisticated emotion detection models.

The existing research on multilabel emotion detection has primarily focused on two different approaches: sequence labeling and sentence classification. Sequence labeling models use a token-by-token approach, labeling each word in the text with emotion. In contrast, sentence classification models identify a number of emotions depending on the text but classify entire sentences based on their dominant sentiment. Both models are significant in multilabel emotion detection. For example, sequence labeling models can identify individual words or phrases that convey certain emotions, while sentence classification models can classify an entire sentence as conveying multiple emotions.

Inspired by previous studies, the researchers sought to evaluate the effectiveness of sequence labeling and sentence classification approaches for multilabel emotion detection in the textual form of data. Moreover, multilabel primary emotions are mapped to complex emotions based on Robert Plutchik's Emotion Wheel.

1.2 Statement of the Problem

1.2.1 General Objective

This research aims to develop sequence labeling and sentence classification models for multilabel emotion detection in text data and map the corresponding complex emotion.

1.2.2 Specific Objectives

The research aims to accomplish the following:

1. Preprocess MEISD Dataset to contain textual instances with 2 identified emotions.

2. Develop Bi-LSTM & BERT-CNN models (Sequence-Labeling & Sentence-Level Classification) for multilabel emotion recognition in text data.
3. Map multilabel emotion to complex emotion using Robert Plutchik's Emotion Wheel.
4. Evaluate the performance of the models using standard evaluation metrics (Precision, Recall, Accuracy, F1-score).

1.3 Significance of the Study

The outcome of this study may be relevant and instrumental to the following parties:

Medical Field (Mental Health and Well-being). One of the main benefits of this study is its potential to help improve mental health and well-being. Accurately detecting multiple emotions in text data can provide valuable insights into individuals' mental health status, enabling healthcare professionals to provide better care and support. For example, identifying a mixture of positive and negative emotions in an individual's text messages or social media posts may indicate that they are experiencing mixed feelings or mood swings, which could be a symptom of bipolar disorder or other mental health conditions.

Business Field (Customer Feedback and Marketing). In customer service, multilabel emotion recognition can help companies quickly identify and address customer issues and concerns, improving customer satisfaction and loyalty. In marketing, emotion recognition can analyze customers' responses to products and services, enabling companies to tailor their marketing strategies better to meet customers' needs and preferences.

Education Field (Student Feedback and Teaching Strategy). In education, multilabel emotion recognition can provide teachers with insights into students' emotional states, enabling them to adjust their teaching strategies accordingly and provide better support.

Overall Advancement of Natural Language Processing. Finally, the proposed study is important because it can contribute to the ongoing development of NLP techniques and improve the accuracy of emotion recognition models. This can lead to the development of more sophisticated and practical NLP applications, significantly impacting various fields and industries.

Researchers. The researchers can develop essential skills such as critical thinking, research methodology, data analysis, and scientific writing, which are essential for their future academic and professional endeavors. The research contributes new knowledge and insights to the field of study, which is valuable for the researchers’ professional development and career advancement.

Future Researchers. The research can provide a better understanding of the performance and effectiveness of sequence labeling and sentence classification methods for multilabel emotion recognition on text data. The findings and insights gained from this study can guide future researchers in exploring similar research questions or developing emotion recognition models for different applications.

1.4 Scope and Limitation

The study essentially revolves around the dataset chosen and the analysis models to be used in sequence modeling and sentence classification for multilabel emotion recognition on text data. Model training and evaluation using standard metrics are also to be considered as well as the usage of Robert Plutchik’s Emotion Wheel to map multilabel emotions into complex ones.

The Multimodal Multi-Label Emotion, Intensity, and Sentiment Dialogue Dataset is chosen for this specific study which is subject to preprocessing, training and testing. As stated in the title of the dataset, it is multimodal, therefore, it contains audio, visual, and textual forms of data. The research will utilize the underrepresented and more challenging form of data in text. The dataset contains 20, 017 instances of English text prior to preprocessing. The dataset is divided into 70% training and 30% testing to serve as input for the models.

The analysis models to be used in the study would be Bi-Directional Long Short Term Memory (Bi-LSTM) and Bi-Directional Encoder Representations from Transformers - Convolutional Neural Network (BERT-CNN) models for sequence labeling and sentence classification respectively. These models are subject to training, testing, and the eventual evaluation for multilabel emotion recognition.

The models used in the study may be less efficient or effective, and other models may yield better results. The labeling of multilabel emotions and mapping of complex emotions in the models rely on Robert Plutchik's Wheel of Emotions for standardization. The study will exclusively employ two primary emotions to be mapped to complex emotional states.

CHAPTER 2
REVIEW ON RELATED LITERATURE

This chapter presents a list of research done with due diligence by others that provide significant insight into the researchers' study. This includes methods that have been researched and applied which have provided the foreground for the researchers' thought processes and methodologies. The publications stated below may or may not be directly related to the current research, but they provide crucial information that supports the study and provide the general gist or background upon which the study is built.

Artificial Intelligence

Artificial Intelligence (AI) has been one of the most significant technological advancements in recent times. The concept of AI dates back to the mid-1950s when pioneers in the field began exploring ways to develop machines that can mimic human intelligence. In recent years, AI has seen unprecedented growth, leading to many breakthroughs in fields such as natural language processing, computer vision, and robotics. In this review, we will examine some of the related literature on AI, its various applications, and its impact on society.

Artificial Intelligence (AI) has become an essential field in modern technology. It involves developing computer systems that can perform tasks that would typically require human intelligence, such as decision-making, speech recognition, and natural language processing. Simplilearn's Introduction to Artificial Intelligence: A Beginner's Guide (2020) provides a comprehensive overview of AI, including its history, applications, and subfields. It emphasizes the importance of AI in various industries, including healthcare, finance, and transportation (Simplilearn, 2020). Additionally, the guide discusses the ethical concerns surrounding AI and its impact on society.

In "A Beginner's Guide to artificial intelligence and machine learning" (2021), M. Tim Jones of IBM introduces the concepts of AI and machine learning (ML) and their applications. The article provides a step-by-step explanation of the process of building an ML model, starting with data collection and ending with deployment. Jones emphasizes the importance of selecting the right algorithm and data to ensure accurate predictions. The article also provides examples of real-world applications of AI and ML in industries such as healthcare, finance, and retail.

Max Roser's "The brief history of artificial intelligence: The world has changed fast – what might be Next?" (2022) provides a historical perspective on AI, tracing its development from its origins in the 1950s to the present day. The article highlights the key milestones in AI research and development, including the development of expert systems and deep learning (Roser, 2022.). Roser also discusses the potential future implications of AI and the ethical concerns that arise with its development, such as the impact on employment and the need for regulation. Overall, the article provides a broad understanding of the evolution of AI and its potential implications for society.

While AI has many potential benefits, it also raises significant ethical concerns. In "Robot Ethics," Patrick Lin, Keith Abney, and George A. Bekey explore the ethical considerations of AI and robotics. The book covers topics such as robot autonomy, responsibility, and the impact of AI on society. The authors argue that as AI becomes more prevalent, we must carefully consider the ethical implications and create policies that prioritize human welfare (Lin et al., 2014).

AI History

Artificial intelligence (AI) has been a field of research since the 1950s, but its history can be traced back to the early 19th century when Charles Babbage developed the first mechanical computer. In the early years of AI research, the focus was on developing algorithms and models that could simulate human intelligence. In the 1960s, the term "artificial intelligence" was coined by John McCarthy, who is considered one of the founders of the field.

One of the earliest successes in AI was the development of the expert system. Expert systems are computer programs that use rules and reasoning to solve problems in a specific domain. The first expert system was developed in the 1970s and was used to diagnose and treat blood disorders. Expert systems have since been used in many other domains, including finance, engineering, and medicine.

In the 1980s, the field of AI shifted towards the development of neural networks. Neural networks are computational models that are inspired by the structure and function of the human brain. They are capable of learning and can be used to recognize patterns in data. Neural networks have been used in many applications, including image and speech recognition, natural language processing, and robotics.

Another major development in AI has been the rise of machine learning. Machine learning is a subset of AI that involves the use of algorithms and statistical models to enable computers to learn from data without being explicitly programmed. Machine learning has been used in many applications, including predictive modeling, fraud detection, and recommendation systems.

In recent years, there has been a surge of interest in deep learning, which is a type of machine learning that uses neural networks with many layers. Deep learning has been used in many applications, including computer vision, natural language processing, and game playing. One of the most famous examples of deep learning is the AlphaGo system, which was developed by Google DeepMind and defeated the world champion in the game of Go.

AI Global Impact

Artificial intelligence (AI) has become an essential tool in modern society, offering numerous benefits to human life. AI can be used to automate repetitive tasks, provide personalized recommendations, analyze large datasets, and even improve decision-making. AI technologies are rapidly changing the way we live and work, and they have the potential to revolutionize many industries.

One of the most significant advantages of AI is its ability to automate tasks that were previously performed by humans. This includes jobs that are repetitive, mundane, or dangerous. For example, AI can be used to automate factory work, reducing the need for human workers to perform repetitive tasks. This can lead to increased productivity, improved safety, and reduced labor costs.

AI can also be used to provide personalized recommendations to consumers. This includes product recommendations on e-commerce sites, personalized content on social media, and even personalized healthcare recommendations. This can lead to increased customer satisfaction, improved engagement, and improved health outcomes.

Another advantage of AI is its ability to analyze large datasets quickly and accurately. This includes analyzing financial data, medical records, and even social media data. This can lead to improved decision-making, better predictions, and improved efficiency.

AI is also being used to improve decision-making in a variety of industries. For example, AI can be used to analyze financial data and make investment recommendations. AI can also be used to analyze medical data and provide personalized treatment recommendations. This can lead to improved outcomes, reduced costs, and improved efficiency.

In 2021, Puneet Kumar, Vinod Kumar Jain, and Dharminder Kumar published a book entitled "Artificial Intelligence and Global Society Impact and Practices". The book discusses the various ways that AI is impacting society on a global level, including in areas such as healthcare, education, finance, and transportation. The authors argue that while AI has the potential to greatly benefit society, there are also significant risks associated with its use, such as job displacement, privacy concerns, and algorithmic bias (Kumar et al., 2021). The book provides a comprehensive overview of the current state of AI and its impact on society, as well as recommendations for policymakers and practitioners to mitigate the potential negative impacts.

In 2019, the Organisation for Economic Co-operation and Development (OECD) published a report entitled "Artificial Intelligence in Society". The report provides an overview of the current state of AI and its potential impact on society, as well as recommendations for policymakers to ensure that AI is developed and deployed in a way that benefits society as a whole. The report highlights the importance of addressing issues such as algorithmic bias, transparency, and accountability in AI systems. It also emphasizes the need for collaboration between different stakeholders, including policymakers, industry leaders, and civil society, in order to develop a shared understanding of the potential risks and benefits of AI and to ensure that its development and deployment are guided by ethical principles (OECD, 2019). Overall, the report provides a comprehensive framework for policymakers and other stakeholders to use in order to ensure that AI is developed and deployed in a way that benefits society as a whole.

Natural Language Processing in Artificial Intelligence

Mishra and Kumar's (2020) book "Artificial Intelligence and Natural Language Processing" provides a comprehensive overview of the current state and future directions of natural language processing (NLP) in the context of artificial intelligence (AI). The authors begin by discussing the historical development of NLP, including the various approaches to language modeling and representation, such as rule-based systems, statistical methods, and deep learning. They then delve into the technical details of NLP, covering topics such as syntax and semantics, text classification, named entity recognition, sentiment analysis, and machine translation.

The book also highlights the current challenges and future directions of NLP in AI. The authors point out that despite the recent advancements in NLP, there are still many challenges that need to be addressed, such as the lack of interpretability and transparency of NLP models, the need for more diverse and representative training data, and the ethical and social implications of using NLP in various applications. The authors also discuss the potential future directions of NLP in AI, such as the integration of multimodal data, the development of more robust and efficient models, and the emergence of more sophisticated applications in various domains, such as healthcare, finance, and education (Mishra & Kumar, 2020).

Overall, Mishra and Kumar's (2020) book provides a valuable resource for researchers, practitioners, and students interested in NLP in the context of AI. The book offers a comprehensive overview of the current state and future directions of NLP, covering a wide range of topics and applications. The authors provide technical details, practical examples, and critical reflections on the challenges and opportunities of NLP in AI, making this book an essential read for anyone interested in this rapidly evolving field.

Natural Language Processing

Natural Language Processing (NLP) is a field of study that deals with the interaction between computers and human language. The goal of NLP is to enable computers to understand, interpret, and generate human language. NLP is a rapidly growing field that has many potential applications, including machine translation, speech recognition, and text analysis. In recent years, advances in machine learning and deep learning have led to significant improvements in the performance of NLP systems.

One of the most significant challenges in NLP is the ambiguity and complexity of human language. Words can have multiple meanings, and the same sentence can be interpreted in different ways depending on the context. NLP systems rely on machine learning algorithms to analyze and process language data, allowing them to recognize patterns and identify relationships between words.

Machine learning and deep learning have become essential tools in NLP. They enable computers to learn from large volumes of data and identify patterns that are difficult for humans to recognize. Deep learning models, in particular, have shown remarkable performance in various NLP tasks, including language translation, sentiment analysis, and text summarization.

NLP has many potential applications in various fields, including healthcare, finance, and marketing. In healthcare, NLP can be used to analyze medical records and assist with diagnosis and treatment. In finance, NLP can be used to analyze news articles and social media to predict stock prices. In marketing, NLP can be used to analyze customer feedback and improve product design and advertising.

In conclusion, NLP is a rapidly growing field with many potential applications. Advances in machine learning and deep learning have led to significant improvements in the performance of NLP systems. NLP has many potential applications in various fields, and its use is expected to grow as more organizations seek to automate language-related tasks.

Natural Language Processing in Artificial Intelligence

Natural Language Processing (NLP) is a subfield of Artificial Intelligence (AI) that deals with the interaction between computers and human language. NLP is used to enable computers to understand, interpret, and generate human language, and it is one of the most critical components of AI. NLP is used in various applications, including speech recognition, machine translation, text analysis, and sentiment analysis.

The integration of NLP in AI systems has led to the development of intelligent virtual assistants, chatbots, and voice-activated devices. These systems use NLP to process language data, enabling them to understand user input and generate appropriate responses. In recent years, AI-powered virtual assistants such as Siri, Alexa, and Google Assistant have become increasingly popular, and they are used in various applications, including smart homes, customer service, and education.

Natural Language Processing (NLP) has gained a lot of attention in recent years due to its potential to revolutionize various industries. In his book "Real-World Natural Language Processing: Practical Applications with Deep Learning", Hagiwara (2021) discusses how deep learning techniques are being used to solve real-world problems in NLP. The author provides practical examples and case studies to demonstrate the effectiveness of deep learning in NLP. He also emphasizes the importance of using appropriate tools and techniques for different NLP tasks.

Another book, "Natural Language Processing Projects: Build Next-Generation NLP Applications Using AI Techniques" by Kulkarni et al. (2021), provides a comprehensive guide to building NLP applications using AI techniques. The authors focus on practical projects that readers can follow along and learn from. The book covers various NLP tasks, such as sentiment analysis, topic modeling, and text classification (Kulkarni et al., 2021). Additionally, the authors provide guidance on choosing the right tools and techniques based on the specific task and data available.

Natural Language Processing (NLP) plays a critical role in many Artificial Intelligence (AI) applications, including affective computing, language translation, and sentiment analysis. NLP enables AI systems to understand, interpret, and generate human language, which is crucial for effective communication between machines and humans. Machine Learning (ML) is another key technology in AI that has a close relationship with NLP. In fact, ML algorithms are often used in NLP tasks such as text classification, named entity recognition, and machine translation. By using large amounts of labeled data, ML models can learn patterns and relationships within the language, allowing them to accurately analyze and process human language in a way that is similar to how humans do. Therefore, the combination of NLP and ML can lead to powerful AI applications that can revolutionize the way we interact with machines and with each other.

Machine Learning

Machine learning (ML) is a subset of artificial intelligence that involves the use of algorithms and statistical models to enable machines to learn from and make predictions on data. It has become an essential tool in various industries and is rapidly changing the way businesses operate. ML allows computers to learn and improve from experience, without being explicitly programmed, enabling them to make better predictions and decisions.

In "A Beginner's Guide to artificial intelligence and machine learning" by Jones (2021) of IBM, the author provides an introduction to the basic concepts and applications of machine learning, including supervised learning, unsupervised learning, and reinforcement learning. The article also covers popular machine learning frameworks and tools such as TensorFlow, sci-kit-learn, and IBM Watson Studio, and provides examples of real-world use cases for machine learning in industries such as healthcare, finance, and manufacturing.

One of the significant advantages of ML is its ability to analyze large datasets. It allows companies to gain valuable insights from large volumes of data, making predictions about future outcomes or identifying patterns in complex data sets. ML can help identify fraud in financial transactions, predict equipment failure in the manufacturing industry, and identify disease patterns in healthcare.

"Natural Language Processing Projects: Build Next-Generation NLP Applications Using AI Techniques" by Kulkarni et al. (2021) is a practical guide for building natural language processing (NLP) applications using machine learning techniques. The book covers a range of NLP topics including text preprocessing, sentiment analysis, named entity recognition, and language translation. It also provides hands-on examples and code snippets using popular machine-learning libraries such as TensorFlow, Keras, and NLTK.

In "Python Machine Learning: Machine Learning and Deep Learning with Python, sci-kit-learn, and TensorFlow 2" by Raschka and Mirjalili (2019), the authors provide a comprehensive guide to machine learning and deep learning with Python. The book covers fundamental machine learning concepts such as decision trees, linear regression, and support vector machines, as well as advanced techniques such as deep neural networks and convolutional neural networks. The authors also provide practical examples and code snippets using popular machine learning libraries such as sci-kit-learn and TensorFlow 2.

ML algorithms have also proven useful in the field of computer vision. With the help of deep learning techniques, computers can detect patterns and objects within images and video data. This technology is being used to improve the accuracy of facial recognition, identify objects in self-driving cars, and improve surveillance systems.

Another advantage of ML is that it can be used to improve the customer experience. Machine learning can be used to analyze customer behavior, identify patterns, and personalize interactions. This includes product recommendations, chatbots, and other forms of interaction with customers.

Furthermore, ML has the potential to transform the way we work. It can automate repetitive tasks, leading to improved efficiency, increased accuracy, and reduced costs. For example, machine learning algorithms can be used to automate repetitive tasks such as data entry, reducing the workload of employees and enabling them to focus on higher-value tasks. Overall, machine learning enhances the capabilities of what we call “natural language processing” (NLP). The following literature depicts ML as an application of NLP.

Machine Learning as Application of Natural Language Processing

Natural Language Processing (NLP) is a branch of Artificial Intelligence (AI) that deals with the interaction between computers and human language. Machine Learning (ML) algorithms are often applied in NLP to develop systems that can understand, analyze, and generate human language. Kulkarni et al. (2021) demonstrate how to build NLP applications using ML techniques, such as text classification, sentiment analysis, and machine translation. They also provide practical examples using popular NLP libraries and frameworks, such as NLTK, spaCy, and TensorFlow.

Beysolow (2018) provides a comprehensive guide to using Python to implement ML and Deep Learning (DL) algorithms in NLP. The book covers essential topics such as text processing, feature extraction, and model selection. It also shows how to use ML techniques to solve real-world NLP problems, such as spam filtering, sentiment analysis, and named entity recognition. The author emphasizes the importance of feature engineering in NLP, which is the process of transforming raw text into meaningful numerical representations that can be used by ML algorithms.

Zhang and Teng (2021) provide a machine-learning perspective on NLP, covering various ML techniques, including supervised, unsupervised, and reinforcement learning. The book also includes advanced topics such as deep learning, neural language models, and natural language generation. The authors provide practical examples using popular NLP datasets and explain how to evaluate the performance of NLP systems. The book is suitable for both researchers and practitioners interested in NLP and ML.

The importance of using ML in NLP cannot be overstated, as ML techniques have significantly improved the accuracy and efficiency of NLP systems. ML algorithms are particularly effective in handling large volumes of text data and learning complex patterns in language. ML techniques have enabled various NLP applications, such as chatbots, virtual assistants, sentiment analysis, and machine translation. As the volume of text data continues to grow, the role of ML in NLP is becoming increasingly critical.

Machine learning has been applied in NLP for a wide range of tasks, including language translation, sentiment analysis, and speech recognition. One of the most significant advantages of ML in NLP is that it allows computers to learn from and improve based on large volumes of data, leading to more accurate predictions and better performance.

One of the most popular approaches to NLP using ML is known as Deep Learning. It is a subfield of machine learning that involves the use of neural networks to learn and process natural language. Deep learning models have shown remarkable performance in various NLP tasks, including language translation, sentiment analysis, and text summarization.

Sentiment analysis is one of the most common applications of ML in NLP. It involves analyzing text data to determine the sentiment expressed by the author. ML algorithms are trained to recognize patterns in language that are indicative of positive, negative, or neutral sentiment. Sentiment analysis has been used in social media monitoring, customer feedback analysis, and product review analysis.

Emotion recognition, also known as affective computing or emotion detection, is the process of identifying and categorizing human emotions through various techniques such as facial expression analysis, voice analysis, physiological signals, and natural language processing. Unlike sentiment analysis which focuses on identifying and classifying opinions expressed in text, emotion recognition aims to detect the underlying emotional state of a person.

While emotion recognition is a promising field, it still faces challenges such as the subjectivity and complexity of emotions, privacy concerns, and the need for large and diverse datasets. Nonetheless, as technology continues to advance and more applications are developed, emotion recognition is expected to play an increasingly important role in our daily lives. The researchers are more than interested in this growing field and would love to add to the existing body of knowledge that encompasses it. An entry into this field brings us to Deep Learning which is said to outperform traditional machine learning techniques in many emotion recognition tasks (Ding et al., 2020).

Deep Learning

Deep learning is a subfield of machine learning that has gained significant attention in recent years due to its ability to extract high-level features from large and complex datasets. Deep learning models are composed of multiple layers of artificial neural networks that work together to analyze and classify data. There have been numerous studies and applications of deep learning across various fields such as computer vision, natural language processing, and speech recognition.

Deep Learning has become a popular technique for solving complex tasks, including natural language processing and computer vision. It has demonstrated impressive performance in various applications such as speech recognition, image classification, and sentiment analysis. However, the success of deep learning models lies not only in their architecture but also in the availability of massive amounts of data for training. Deep Learning models, particularly neural networks, can learn from large datasets, automatically extract relevant features, and make accurate predictions. As a result, researchers have been able to achieve state-of-the-art results in emotion recognition tasks using deep learning models.

Deep Learning Model

Deep learning has revolutionized the field of machine learning by enabling the creation of highly complex models that can learn and extract features automatically from data. Table 1 contains commonly used deep learning models for emotion recognition:

Table 1

Common Deep Learning Models for Emotion Recognition.

Deep Learning Model	Advantages	Disadvantages
Recurrent Neural Network (RNN)	Captures sequential information	Prone to vanishing gradients and overfitting

Long Short-Term Memory (LSTM)	Overcomes vanishing gradient problem of RNNs	Computationally expensive
Gated Recurrent Unit (GRU)	More computationally efficient than LSTM	Not as effective as LSTM in capturing long-term dependencies
Convolutional Neural Network (CNN)	Effective in capturing local features	Not as effective in capturing global dependencies
Transformer	Highly effective in capturing long-term dependencies	Requires large amounts of training data and computational power

Several studies have also evaluated the performance and efficacy of deep learning models in various applications. For example, in NLP tasks, CNNs have shown higher accuracy than traditional machine learning models such as Support Vector Machines (SVM) in sentiment analysis, while LSTMs have achieved state-of-the-art performance in language modeling tasks such as speech recognition. In image recognition tasks, CNNs have surpassed human-level performance in certain domains.

Deep Learning Applications

One area where deep learning has shown significant promise is image classification. Deep convolutional neural networks (CNNs) have been successfully applied to tasks such as object detection, facial recognition, and image segmentation. The use of CNNs has been shown to outperform traditional machine learning techniques in these applications. For example, a deep CNN was used to classify images from the ImageNet dataset and achieved state-of-the-art results in image recognition tasks (Annis et al., 2021).

In addition to image classification, deep learning has also shown great potential in natural language processing (NLP) tasks. Recurrent neural networks (RNNs) have been applied to tasks such as language modeling, speech recognition, and machine translation. One notable application of RNNs is in the field of chatbots, where they are used to generate human-like responses. In a study, a deep RNN was used for machine translation and outperformed traditional statistical machine translation models (Sutskever & Hinton, 2010).

Another area where deep learning has been applied is in the field of health care. Deep learning models have been used to diagnose diseases from medical images, predict patient outcomes, and even generate personalized treatment plans. For example, a CNN was trained to identify diabetic retinopathy from retinal images, achieving a level of accuracy on par with that of human experts (Farooq et al., 2022).

In the study by Divya Vani Lakkireddy, a supervised machine learning approach is used for the recognition of emotional tones from speech and text data. The study employed deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) for the classification of emotions. The results demonstrated that the integration of speech and text data improved the accuracy of the emotion recognition system.

Furthermore, domain-specific lexicon generation has been shown to be effective in emotion detection from text data. In the study by Bandhakavi et al. (2017), a domain-specific lexicon is generated for emotion detection from text. The study utilized deep learning models such as Word2Vec and Support Vector Machines (SVM) for the classification of emotions. The study demonstrated that the use of domain-specific lexicons improved the performance of emotion detection models, especially for domain-specific text data.

The following papers showcase the effectiveness and potential of Deep Learning models in Text Emotion Recognition. The study by Jabreel and Moreno (2019) presents a deep-learning approach for multi-label emotion classification in tweets. The research uses Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models, which outperform traditional machine learning techniques in terms of accuracy and efficiency. Another study called "Text-based emotion detection: Advances, challenges, and opportunities" by Acheampong et al. (2020) provides an overview of the latest advancements and challenges in Text-based Emotion Detection. The paper also highlights the potential of deep learning models in the field, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. Finally, a study by D. H. Zhang et al. (2020) introduces a multi-modal approach to emotion detection, which combines text and image data. The study utilizes a deep learning model, specifically the Multi-Modal Deep Boltzmann Machine (MM-DBM), to capture the interdependencies between modalities and labels.

Overall, the aforementioned papers demonstrate the potential of deep learning models in emotion recognition tasks, particularly in text data. CNN, RNN, LSTM, and GRU models are effective in handling text data and can provide accurate and efficient results.

Sequence labeling and sentence classification are important tasks in deep learning and emotion recognition. Sequence labeling models are used to predict labels for each element in a sequence, such as predicting the part of speech of each word in a sentence or detecting emotions for each word in a text. Both sequence labeling and sentence classification can be used for multi-label emotion recognition in text data.

For sequence labeling, a common approach is to use a Bidirectional Long Short-Term Memory (BiLSTM) network with a Conditional Random Field (CRF) layer on top. This allows the model to capture the sequential nature of the input text and predict multiple labels for each word or token in the input sentence. Hossain, E., et.al. (2021) elaborate where the study on sentiment analysis of restaurant reviews using a deep learning approach. In this study, the authors propose a deep learning model called SentiLSTM, which uses the BiLSTM network to analyze the sentiment of restaurant reviews. The model was trained and evaluated on a dataset of restaurant reviews from Yelp and was compared with other state-of-the-art sentiment analysis models.

The authors report that their proposed model achieved high accuracy in sentiment analysis, outperforming other models on the Yelp dataset. Specifically, the authors reported an accuracy of 91.35%, a precision of 93.1%, a recall of 91.33%, and an F1 score of 92.21%.These performance metrics suggest that the SentiLSTM model is effective at classifying restaurant reviews as either positive or negative based on their sentiment. They also note that their model has the advantage of being able to capture long-term dependencies in the review text, which is important for accurately identifying sentiment in natural language.

Overall the SentiLSTM model uses the BiLSTM network for sentiment analysis, which gives useful architecture to consider for the research in the sentiment analysis tasks. Another study by Asghar et al. (2022) proposes a deep neural network architecture for detecting and classifying emotions in textual content. The authors used a Bidirectional Long Short-Term Memory (BiLSTM) model for the detection and classification of emotions from the textual content. They pre-processed the input data by tokenizing the text and encoding it using the GloVe word embedding. The BiLSTM model was trained on the pre-processed data to predict the emotion labels for each input text. They also evaluated the performance of the model on several metrics, including accuracy, precision, recall, and F1-score. The results showed that the BiLSTM model achieved better performance compared to other machine learning models, such as Support Vector Machines (SVM) and Naive Bayes (NB).

For sentence classification, Convolutional Neural Networks (CNNs) have been shown to be effective in multi-label text classification tasks, including emotion recognition. In this approach, the model takes the entire input sentence as input and uses filters to extract features from the sentence, followed by fully connected layers to predict the multiple labels. The study by Abas, A., et al. (2022) proposes a deep learning model called BERT-CNN for detecting emotions from the text. The BERT-CNN model consists of a pre-trained BERT (Bidirectional Encoder Representations from Transformers) model followed by a Convolutional Neural Network (CNN) for feature extraction and classification. The pre-trained BERT model is fine-tuned on the input data, and the CNN is trained on the output of the BERT model to predict the emotion labels.

The study used the SemEval 2018 Task 1 dataset, which contains tweets annotated with six emotion labels, namely anger, joy, sadness, fear, surprise, and disgust. The BERT-CNN model achieved an F1 score of 0.705 on the test set, outperforming several state-of-the-art models. The study also conducted ablation experiments to analyze the contribution of each component of the BERT-CNN model, showing that both the pre-trained BERT model and the CNN are crucial for achieving high performance in emotion detection from text.

Both approaches have their own strengths and weaknesses and the choice between the two depends on the specific requirements of the task and the characteristics of the dataset.

Sequence Labeling

Sequence labeling is commonly used in emotion detection because it allows for a more fine-grained analysis of the emotional content in a text. By assigning emotional labels to each word or token in a sequence, sequence labeling can capture the nuances of emotional expression that may be missed by sentence-level analysis.

Mauajama, F., et.al. (2020) elaborates their dataset as consisting of multi-turn conversations, in which each turn is labeled with multiple emotion labels. They used a sequence labeling approach to assign emotion labels to each word or phrase within each turn, allowing for more fine-grained labeling at the word or phrase level. The authors first tokenized each turn into words or phrases. They then annotated each token with one or more emotion labels, where each label corresponds to a specific emotion. The authors used a total of 11 emotion labels: anger, fear, disgust, sadness, joy, surprise, neutral, excitement, frustration, boredom, and hope.

Table 2

Sample Emotion and Sentiment Distribution

Utterance	Emotion	Sentiment
And live forever as a machine!	Disgust	Positive
Look at you, all jealous.	Joy	Negative
Brain tumors at her age are highly unlikely	Sadness	Positive
Your political consultants have written you a nice story	Disgust	Positive
I bet it was one of her backstabbing rivals	Acceptance	Negative

However, the authors also used sentence-level classification to predict the sentiment polarity of each turn in the conversation, which is separate from their emotion recognition task. They used the precision, recall, and F1-score metrics to evaluate the performance of their model for both the sequence labeling and sentence classification tasks.

Sentence-level Classification

In the study by Lim et al.(2022), the authors used a sentence-level classification approach rather than sequence labeling to recognize emotions in unstructured conversation data. The authors used LSTM, CNN-LSTM, and attention to classify each sentence in the dataset into one of the following six emotion categories: joy, anger, sadness, fear, disgust, and surprise. The CNN was trained on preprocessed text data, which included sentence embedding vectors and feature vectors such as sentence length and word frequency. Overall, the study by Lim et al. used sentence-level classification with a multilabel approach to recognize emotions in unstructured conversation data.

The deep learning model used LSTM, CNN-LSTM, and attention, which are widely used in text emotion classification studies. As for the evaluation method, accuracy, precision, recall, and F1-score were used focusing on representative emotions. The authors concluded that among the proposed three deep learning models, the attention model showed the best performance with 65.9% using a sentence-level classification approach with a multilabel approach. The authors used a dataset of unstructured conversation data, which consisted of 2,197 sentences with one or more emotion labels assigned to each sentence. The emotions included in the dataset were joy, anger, sadness, fear, disgust, and surprise.

Overall, the study by Lim et al.(2022), demonstrates the sentence-level classification approach with a multilabel approach for emotion recognition in unstructured conversation data.

Emotion Recognition

Deep learning has been applied extensively in emotion detection, particularly in the context of text analysis. One of the main approaches to utilizing deep learning in this domain is through the use of deep neural networks, which can be trained on large datasets of annotated text in order to learn patterns and relationships between words and emotions.

One common approach to using deep learning for emotion detection in the text is through the use of convolutional neural networks (CNNs). CNNs are a type of deep neural network that can automatically learn to detect and extract features from input data, such as images or text. In the context of text analysis, CNNs can be used to analyze the relationships between words and emotions and to identify patterns and features that are associated with specific emotions.

Another approach to using deep learning for emotion detection in the text is through the use of recurrent neural networks (RNNs), which are capable of processing sequential data such as text. RNNs can be used to model the temporal dependencies between words in a sentence or document, allowing them to capture more complex relationships between words and emotions. Long Short-Term Memory (LSTM) networks, a type of RNN, have been particularly successful in this context.

Other deep learning approaches have also been applied to emotion detection in the text, such as the use of autoencoders, which can be used to learn a compressed representation of text data that can then be used to detect emotions. Variational autoencoders (VAEs) have been shown to be particularly effective in this domain, as they can learn to model the distribution of emotions in a more flexible way than traditional autoencoders.

Overall, deep learning has shown great promise in the field of emotion detection in text. The ability of deep neural networks to automatically learn and extract features from text data, combined with the availability of large annotated datasets, has enabled significant advances in this domain.

Robert Plutchik’s Wheel of Emotions

Robert Plutchik's Wheel of Emotions is often used as a theoretical framework for multi-label emotion classification because it proposes a comprehensive and universal set of eight basic emotions, which are joy, sadness, anger, fear, trust, disgust, anticipation, and surprise. These basic emotions can be combined to form more complex emotions, making it a useful tool for representing a wide range of emotional states. Additionally, the Plutchik model suggests that emotions are not discrete, but rather exist along a continuum of intensity, providing a more nuanced approach to emotion detection and classification. This approach can better represent the variety and richness of emotions that are present in natural language and can help in accurately detecting emotions in real-world scenarios. On the other hand, a single emotion labeling approach may oversimplify the complexity of emotions and may not be able to capture the nuances of emotions that are present in a text.

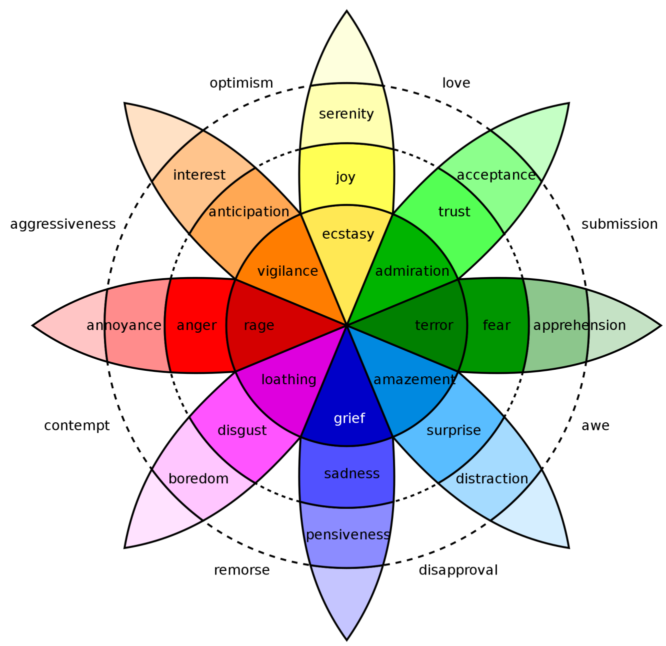


Figure 1. Robert Plutchik's Wheel of Emotion

In the paper "A Deep Learning-Based Approach for Multi-Label Emotion Classification in Tweets" by Jabreel, M., & Moreno, A. (2019), the authors used Plutchik's wheel of emotions to categorize emotions into a multi-label framework because it provides a comprehensive and widely used framework for understanding and classifying emotions. The wheel categorizes emotions into eight primary emotions, which can be combined to form more complex emotions. By using Plutchik's wheel, the authors were able to create a more nuanced and comprehensive classification system for emotions in tweets, which can help in understanding the complexities of human emotions expressed on social media

Therefore, using the Plutchik wheel of emotion as a basis for multi-label emotion classification can help to standardize the classification process and facilitate the comparison of results across different studies.

CHAPTER 3
TECHNICAL BACKGROUND

This chapter contains the definition of technical terms used in prior chapters or to be used in the upcoming chapters. The said terminologies shall range from terminologies in the field of Computer Science and the field of Linguistics.

Emotion

According to (Merriam-Webster, n.d.), the term “emotion” is a noun used to describe a conscious mental reaction (such as anger or fear) subjectively experienced as a strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioral changes in the body. Emotions are defined in various ways depending on who you ask. One might say that emotions are biological states that come about as a result of thoughts, feelings, and behaviors. Emotions may also exist on a continuum from pleasure to displeasure. But emotion theorists largely disagree on the definition of what an emotion is (Davis, n.d.).

Theory of Emotion

Emotion theory proposes that human beings have a limited number of emotions (e.g., fear, anger, joy, sadness) that are biologically and psychologically “basic” (Wilson-Mendenhall et al., 2013), each manifested in an organized recurring pattern of associated behavioral components (Russell, 2006).

Emotion Detection Technology

Emotion detection is the task of recognizing a person’s emotional state — for example, anger, confusion, or deceit across both voice and nonvoice channels. The most common technique analyzes the characteristics of the voice signal, with word use as an additional input, if available (Gartner, 2023).

Data Set

A data set is a collection of responses or observations from a sample or entire population (Bhandari, 2023). For example, an emotion may be defined in terms of its tone, facial expression, and sentence.

Preprocessing

A preprocessing in Machine Learning refers to the technique of preparing, cleaning, and organizing the raw data to make it suitable for building and training Machine Learning models. It is a data mining technique that transforms raw data into an understandable and readable format (Goyal, 2022).

Text Data

Text data refers to all empirical materials that exist in textual form, be they produced through writing or through transcription from speech (Eriksson & Kovalainen, 2008). Examples of text data are Publishing Dictionaries, grammar books, teaching materials, usage guides, and thesauri.

Deep Learning Model

Deep Learning is a type of machine learning and artificial intelligence (AI) that imitates the way humans gain certain types of knowledge. Deep learning is an important element of data science, which includes statistics and predictive modeling (Burns & Brush, 2021).

Algorithm

According to Oxford, an algorithm is a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer. The recipe for baking a cake, and the method we use to solve a long division problem are examples of an algorithm. Algorithms are widely used throughout tech-related industries.

Natural Language Processing

Natural Language Processing is a branch of artificial intelligence or AI—concerned with giving computers the ability to understand the text and spoken words in much the same way human beings can (IBM, 2023). Natural language processing is the driving force behind machine intelligence in many modern real-world applications.

Machine Learning

Machine learning is a subfield of artificial intelligence, which is broadly defined as the capability of a machine to imitate intelligent human behavior (Sloan, 2021). Machine learning is the core of some companies' business models, like in the case of Netflix's suggestions algorithm or Google's search engine. Other companies are engaging deeply with machine learning, though it's not their main business proposition (Brown, 2021).

Artificial Intelligence

Artificial Intelligence (AI) is making robots think and act intelligently. Artificial intelligence's goal is to develop ideas and methods that can enable machines to comprehend in the same way that people can, particularly when doing jobs (Artasanchez & Joshi, 2017).

Model

The output of a model is a file. The model is created and taught to be either descriptive to learn from data or predictive to make predictions about the future, or it can be trained to do both (Alpaydin, 2019).

Sequence Labeling

Sequence labeling is a Natural Language Processing task. It is a type of pattern recognition task that involves assigning labels to each element of a sequence of tokens in a sentence. The sequence of tokens could be individual words, phrases, or even characters. It aims to classify each token (word) in a class space C. This classification approach can be independent (each word is treated independently) or dependent (each word is dependent on other words) (Bilici, 2021). Sequence labeling is a fundamental task in many NLP applications, including information retrieval, text classification, sentiment analysis, and machine translation.

Sentence Classification

Sentence classification refers to the process of categorizing sentences into different classes or categories based on their content, context, and purpose. It is a natural language processing (NLP) technique that involves analyzing the text and assigning labels or tags to the sentences to identify their meaning or intent. Sentence classification is one of the simplest NLP tasks that have a wide range of applications including document classification, spam filtering, and sentiment analysis (Sengupta, 2021).

CHAPTER 4
DESIGN AND METHODOLOGY

This chapter details the tools and procedures to be undertaken to aid the researchers in their efforts in solving computing problems. This includes the conceptual framework, analysis and design, and development model, as well as the schedule allocated in designing, developing, and testing the intended system, as well as the roles and tasks delegated to the researcher's proponents.

4.1 Research Environment and Respondents

The dataset is acquired online. The data used in the study are collected from an existing study done by Firdaus, M. et al. (2020). The Indian Institute of Technology Patna provides the data set upon request via electronic form interaction. The dataset contains over 1,125 dialogues and more than 20,000 utterances and contains 15 attributes. However, in this study, the focus is placed on the utterances that contain two emotions. This is in line with the study's objective to detect multiple emotions and for that to be accomplished, two emotions are necessary.

4.2 Research Instrument or Sources of Data

The study uses existing data that contains multi-modal data, including text, audio, and visual cues, which were collected from conversations between two individuals in various scenarios such as interviews, group discussions, and casual conversations from selected TV series. The research will utilize the underrepresented and more challenging form of data in text. The dataset is designed for emotion recognition and sentiment analysis in conversations. It contains 15 attributes which include annotations for multiple emotion labels, intensity levels, and sentiment polarities.

The data set is obtained upon request from the Indian Institute of Technology Patna through electronic form correspondence. This study will only be utilizing the textual data in this dataset in correspondence with the study's objectives and limitations.

Table 3.

Instances of Data from the MEISD Dataset

TV Series	Utterances	uttr_ids	sentiment	emotion	intensity	emotion2	intensity2	emotion3	intensity3
GA	like i said	9	negative	acceptance	1	disgust	1		
GA	i'm screwed	10	negative	disgust	2	sadness	1		
GA	okay, martin, robinson, bond, hawkins	11	neutral	neutral					
GA	only 6 women out of 20	12	negative	surprise	2	disgust	1		
GA	yeah. i hear one of them's a model	13	negative	disgust	2	sadness	1		
GA	seriously, that's gonna help with the respect thing?	14	negative	surprise	2	disgust	3		

The dataset contains over 1,125 dialogues and more than 20,000 utterances, making it a substantial resource. The study will only be utilizing 10 attributes out of 15 attributes that are relative to this study which is shown above in the table.

4.3 Research Procedure

4.3.1 Gathering of Data

1. Extensive research on related literature for the proposed research topic.
    a. Research revolving around emotion recognition.
    b. Focused on studies using textual data.
    c. Narrowed research down to multilabel emotion recognition.
2. Identifying which dataset provides ideal conditions for the success of our topic based on related literature.
    a. Listed all datasets in related literature significant to the study that met certain criteria:
        i. Multiple emotions
        ii. Textual data
        iii. Based on previous studies
        iv. A sample size of 1000 or more
    b. Selected study most appropriate for the researchers' study.
3. Preprocessing dataset to tailor-fit thesis data requirements (specified in the following section).

4.3.2 Treatment of Data

The study will use the MEISD data set. The data were initially stored and organized as CSV files. Preprocessing is to be done to the dataset to utilize text instances that contain two (2) emotions. This is in line with the study's objective to detect multiple emotions and for that to be accomplished, two (2) emotions are necessary which also corresponds to the following step:

Attributes that are not relative to the study are discarded as well as rows with single emotion are also to be dealt with. The MEISD dataset is to be duplicated as sequence labeling and sentence classification models require separate preprocessing techniques. Conversion of all text to lowercase to standardize input has already been done.

The recommended preprocessing method for Bi-LSTM (Bidirectional - Long Short-Term Memory) models in natural language processing is tokenization. Tokenization is the process of breaking text into smaller units, typically words or subwords, for further analysis. This allows the Bi-LSTM model to process and analyze each word or subword as a separate input, and better capture the context and meaning of the text.

The recommended preprocessing method for BERT-CNN (Bidirectional Encoder Representations from Transformer - Convolutional Neural Networks) involves the use of the WordPiece tokenizer, which is a subword tokenization algorithm. This tokenizer breaks down words into smaller subwords, allowing the model to handle out-of-vocabulary words and capture more fine-grained linguistic information.

The data set is split into a training set and a testing set. The training set undergoes training using both deep learning models specified to determine their multilabel emotions. The testing will be used to evaluate the performance of the two models.

4.4 Conceptual Framework

This study anchors classifying complex emotions from the dataset acquired. This study attempts to compare the recognition capabilities of Deep Learning Models for multi-label emotions based on the words from a certain sentence provided. The conceptual framework depicted below is composed of 3 groups - *Data Preprocessing, Word Embedding Generation*, *and Developing an Emotion Recognition Model*.

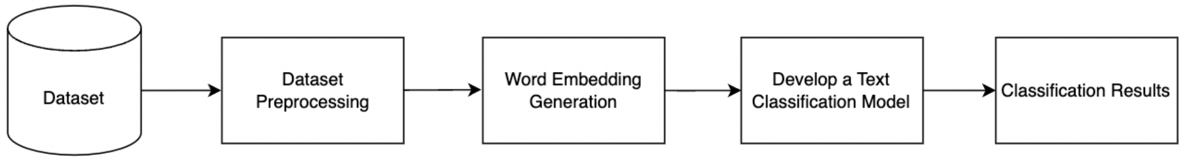


Figure 2. Illustration of the entire Conceptual Framework of the Study

Figure 2 shows the general process of how this study is done. The Dataset is first preprocessed. For word embedding generation, the dataset is partitioned into training data and testing data. The training set will be used in BERT and creating Word2Vec word embeddings, and are used as an input for the sentence classification model and sequence labeling model respectively. After training the model with the given training data, the model will then be tested with the testing data. Classification results will then be measured through performance metrics such as accuracy, precision, recall, and f1 score.

4.5 Analysis and Design

Figure 3 illustrates the first part of the conceptual framework, which is *Dataset Preprocessing*.

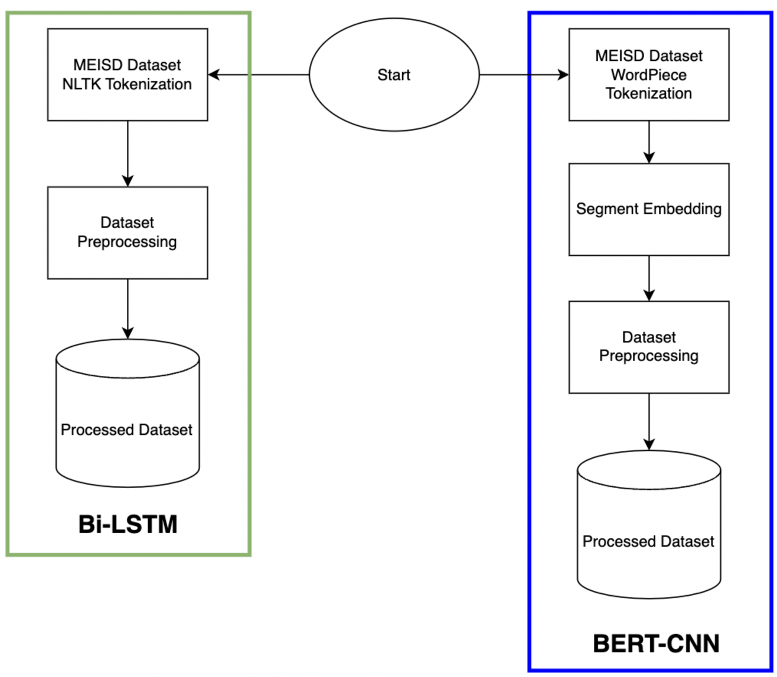


Figure 3. Dataset Preprocessing for Both Models

The MEISD dataset that the researchers acquired will undergo preprocessing and due to the different architectures of the models, BERT-CNN and Bi-LSTM preprocessing will have some key differences. Both models start by tokenizing the input text to split it into individual words or subwords. Bi-LSTM will use the NLTK tokenizer, while BERT-CNN uses the WordPiece tokenizer. After the preprocessing steps have been completed, the output will be the processed dataset for each model. This preprocessed dataset can then be used to train the respective models. Overall, the preprocessing steps are crucial for preparing text data for these models and can significantly impact their performance on downstream tasks.

After preprocessing the MEISD dataset, it is then split into Training and Testing. The Training Set will be used for the next step for both BERT-CNN and Bi-LSTM models to generate respective word embeddings using their specific techniques. For BERT-CNN, this involves generating contextualized word embeddings using the pre-trained BERT model, while for Bi-LSTM, this involves generating word embeddings using a trainable embedding layer that maps each word to a dense vector representation.

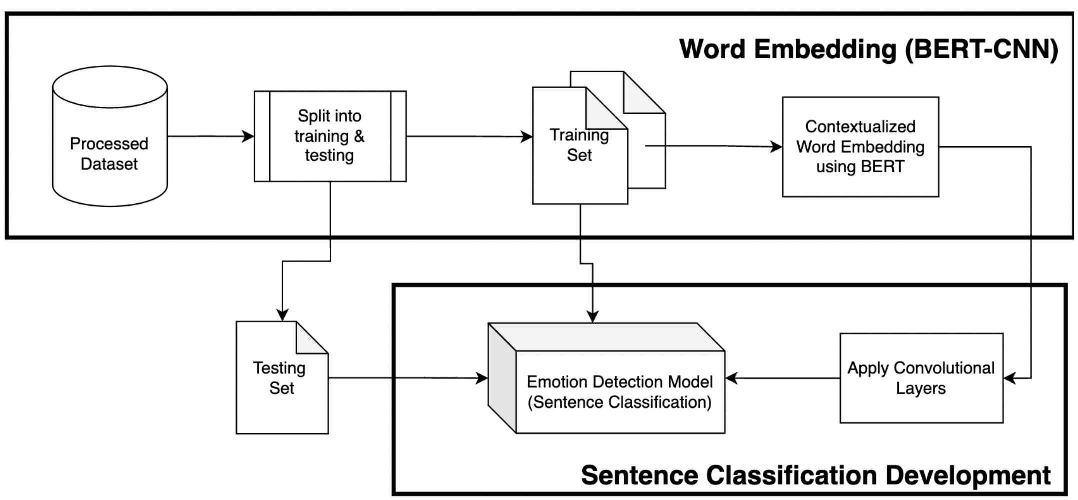


Figure 4. Word Embedding Generation and Development for Sentence Classification Model

In BERT-CNN, contextualized embeddings are generated using the BERT pre-trained language model. BERT uses a transformer-based architecture that takes into account the entire sentence context to generate contextualized word embeddings. These embeddings capture both the syntax and semantics of the word in the context of the sentence. The BERT-CNN model applies a series of convolutional layers to the embeddings. The convolutional layers help to extract higher-level features from the embeddings and identify important patterns in the data. Training data is then used as an input to the created text classifier to train. The text classifier is created using CNN architecture. Once training is finished, the text classification model has been created and will be tested using the Testing Set.

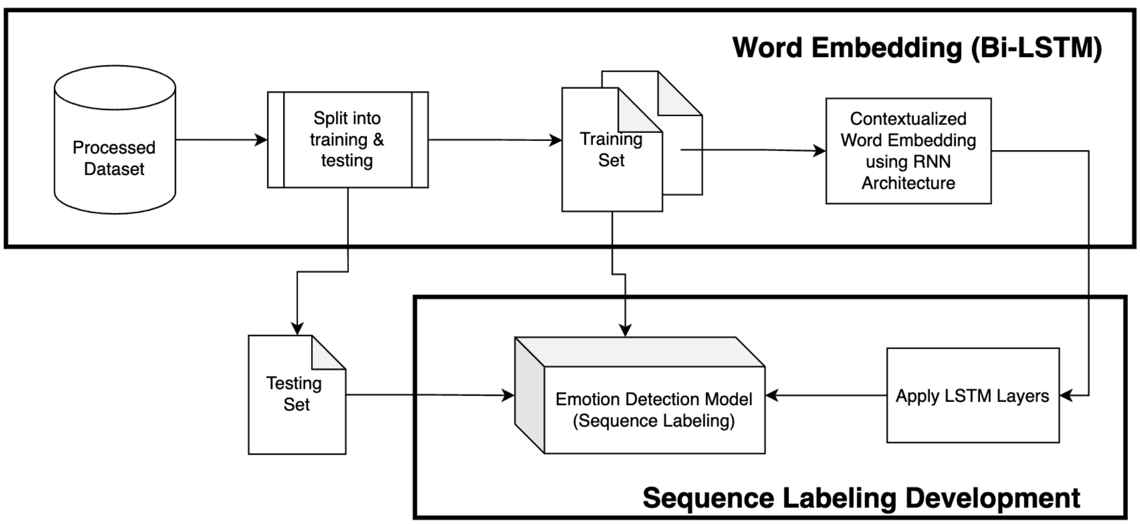


Figure 5. Word Embedding Generation and Development for Sequence Labeling Model

In contrast, Bi-LSTM generates contextualized embeddings using a recurrent neural network (RNN) architecture. Bi-LSTM processes the input sequence in both forward and backward directions, allowing it to capture contextual information from both the past and future words in the sequence. The resulting contextualized embeddings capture the sequential nature of the input text. Similar to the process of BERT-CNN after creating the model, the training data is then used as input to the created text classifier to train.

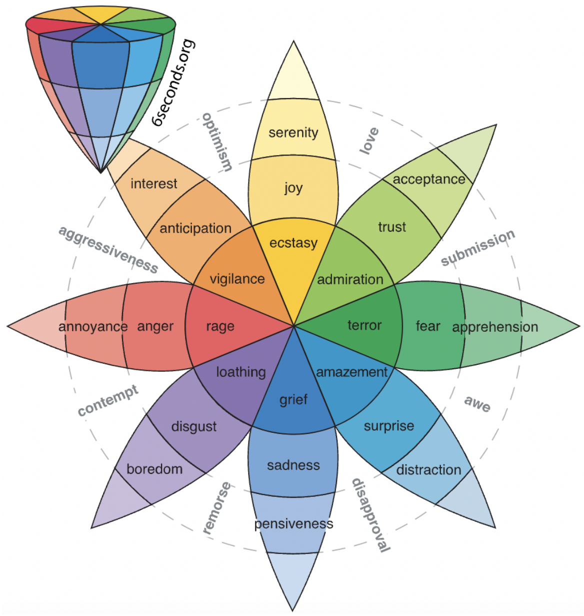
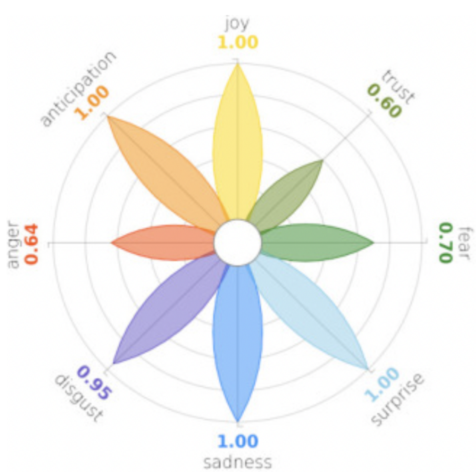


Figure 6. Robert Plutchik's Wheel of Emotion with three degrees of intensity

After the emotion classification is done by the model, the output can be compared with the different emotions on the wheel to get a more nuanced understanding of the emotions being expressed in the text.




```
from pyplutchik import plutchik

emo = {
    'joy': 1,
    'trust': .6,
    'fear': .7,
    'surprise': 1,
    'sadness': 1,
    'disgust': .95,
    'anger': .64,
    'anticipation': 1
}

plutchik(emo)
```

Figure 7. Sample emotion mapping and generation using PyPlutchik

The researchers will then use a Python library, PyPlutchik, which provides functions for both single emotion classification and batch processing of multiple emotion labels. It provides a simple and easy-to-use interface for mapping the output of an emotion detection model to the different emotions represented in the Plutchik wheel.

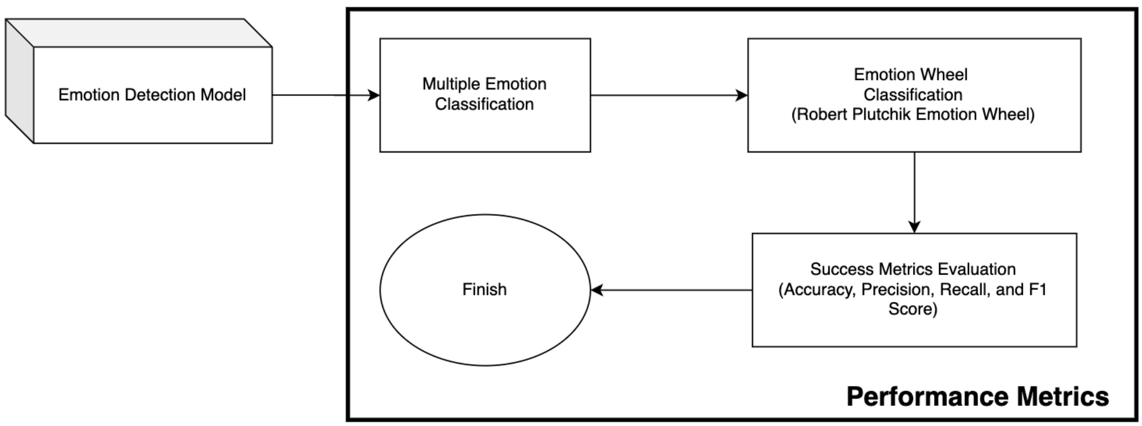


Figure 8. Performance Metrics for the Developed Models

Once the emotion detection models are trained and tested using appropriate datasets, the output can be evaluated using various metrics using the Robert Plutchik Emotion Wheel, which is a guide for determining complex emotions. After that, performance metrics such as accuracy, precision, recall, and f1 score will be measured and used to see the overall performance of the model. K-fold Cross-Validation will also be performed along with the performance metrics mentioned to validate how well the model performs with the dataset overall and to check whether or not the model performs consistently.

4.6 Development Model

The Waterfall technique, often referred to as the Waterfall model, is a sequential development process that moves like a waterfall through all project phases, with each phase finishing up completely before the start of the next.

The waterfall method is a popular and widely-used project management framework that is characterized by a sequential, linear approach to development (Hughey, 2009). The waterfall model is based on a clear and structured set of steps that must be completed in a sequential manner, from initial requirements gathering to design, implementation, testing, and maintenance.

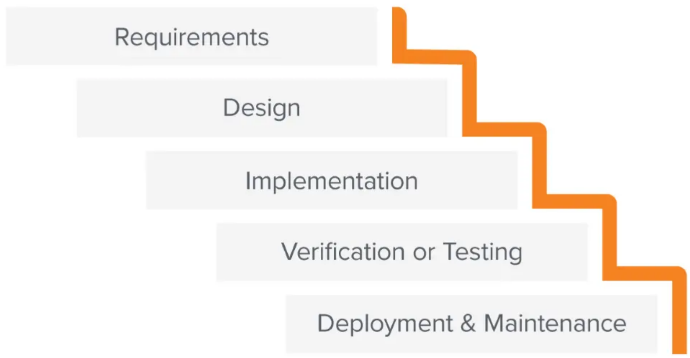


Figure 9. Waterfall Method

Figure 9 shows the beauty of the waterfall method lies in its ability to provide a clear roadmap for the entire development process, ensuring that each stage is completed before moving onto the next.

The research begins with the Requirements phase where Thesis Topic Ideation was initialized and finalized when the ideal dataset was obtained. This was then followed with exhaustive research on the topic.

Design phase began with Thesis Definition and Planning where research on the proposed topic was extensively done. This revolved around related literature and technical background which was necessary to obtain the target objectives of the study. Related literature provided great insight into methodologies that the researchers may implement in the study to provide a certain level of standardization and authenticity. This stage was finalized after a successful proposal of the study to a panel of experts on the field who would provide necessary revisions before implementation may begin.

Implementation begins with the preprocessing of the dataset. Training and testing of the models will be included in the process once the development of the models have been completed. Results obtained will undergo scrutiny for the evaluation of model performance under deployment and maintenance. Valuable information obtained from these phases will be essential for the documentation of the study which involves results, discussions, and recommendations.

4.7 Development Approaches

The development of this research will utilize the bottom-up development approach. It is a strategy used in software development where the project is built by starting with the smallest and simplest components and gradually integrating them into larger and more complex systems. This approach is applicable to the research study as the study is achieved by combining the processes shown below.

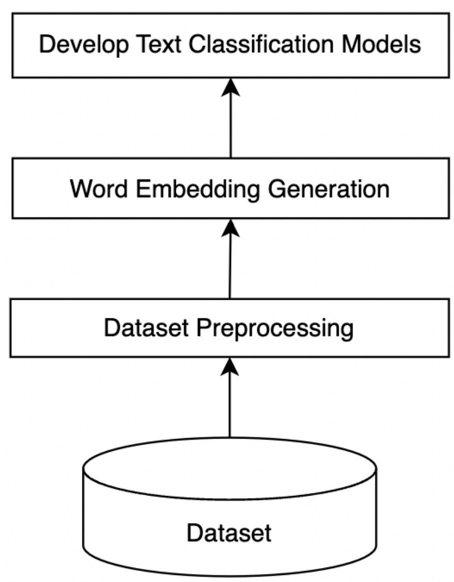


Figure 10. Bottom-up Development Approach

Figure 10 shows the approach taken by the research. Each module is designed to meet a specific function or task, and it is essential for the succeeding modules to have access to these functionalities or their vital outputs. Therefore, the modules must be developed in a specific order, with each one required by the succeeding module to ensure that the entire system functions as intended. The system and model are dependent upon the dataset obtained. The data is then preprocessed accordingly and word embedding generation follows. The data is then divided into training and testing sets. Both training and testing are performed on the chosen models. Evaluation is to be done on the testing set to determine the performance of both models.

4.8 Software Development Tools

This section specifies the available technological tools being used by the researchers for the successful implementation of this study. The list of tools is as specified below in Table 4:

Table 4

Software Development Tools

Software	Version	Purpose
CoLab	N/A	A free online platform provided by Google for running Python code in a web browser. Allows users to write and execute Python code, store and analyze data, and collaborate with others in real time.
GitHub	3.81	A code-hosting version control platform intended for collaboration in software and system development.
GitHub Desktop	3.2	An application that enables you to interact with GitHub using a GUI instead of the command line or a web browser.

Google Chrome	111.0.5563.110	Software is used to access sites and use Google Colab and Google Workspace.
Hugging Face	4.28.1	An open-source library that provides APIs and tools to easily download and train state-of-the-art pre-trained models.
InstaGantt	N/A	A web-based project management tool used for creating Gantt charts.
NLTK (Natural Language ToolKit)	3.7	Human language data for applying statistical natural processing language
PyPlutchik	0.0.11	Designed for the visualization of Plutchik's emotions in texts or in corpora.
Python	3.11	A high-level, interpreted programming language that is popular for its simplicity, readability, and ease of use. Used for Machine Learning.
PyTorch	2.0	A platform for building and training deep neural networks.
TensorFlow Hub	N/A	A repository of trained machine learning models ready for fine-tuning and deployable anywhere.
Visual Studio Code	1.76	A code editor used in creating systems and software.

4.9 Project Management

This section discusses the schedule and timeline, responsibilities, budget, and cost management of the team at the time of the development of the research project. Each subsection discusses its purpose as well as the reason for the decision made in the management of the project.

4.9.1 Schedule and Timeline

This section lists the timetable that the researchers adhered to in order to meet submission requirements and internal research deliverables. The actions and deliverables that must be completed in order to produce a thesis proposal within the second semester of the academic year 2022-2023 are listed in Table 5.

Table 5

Gantt Chart of Activities, Second Semester, SY 2022 - 2023

SECOND SEMESTER, A.Y 2022 - 2023															
Tasks			February				March				April				
			1	2	3	4	1	2	3	4	1	2	3	4	
1	Thesis Topic Ideation	Research Problem Identification													
		Proposal of initial Topic													
		Topic Finalization													
2	Thesis Definition & Planning	Chapter 2: Review on Related Literature													
		Chapter 3: Technical Background													
		Research Objectives													
		Chapter 4: Design & Methodology													
3	Thesis Development	Appendices & Curriculum Vitae													
		Abstract													
		Chapter 1: Introduction													
4	Thesis Revision	Proposed Document Draft													
		Draft Revisions													
		Agreement Letter													
5	Thesis Defense	Sworn & Recommendation Letter													
		Thesis Paper Submission													
		Thesis Proposal Defense													
		Rubrics Submission													
		Thesis Paper Revisions													
		Revised Thesis Paper Submission													
6	Consultations	Thesis Adviser Weekly Consultation													

Table 6

Gantt Chart of Activities, First Semester, SY 2023 - 2024

FIRST SEMESTER, A.Y 2023 - 2024															
Tasks			June				July				August				
			1	2	3	4	1	2	3	4	1	2	3	4	
1	Data Training	Preprocessing Dataset													
		Training the algorithm with the obtained dataset													
		Testing the model													
2	Model Testing and Verification	Accuracy Testing													
3	Thesis Documentation	Chapter 5: Results and Discussions													
		Chapter 6: Conclusions													
4	Research Conference	Research Conference Registration													
		Research Conference Defense													

Table 6, on the other hand, displays the timetable table, which specifies the workflow to be followed during the thesis' second half of completion. The training of the algorithm, as well as the testing, verification, and validation of the accuracy of the produced results as well as research conference, are all part of the second half's actual implementation of the proposed system/algorithm.

4.9.2 Responsibilities

To ensure that submission deadlines and deliverables are fulfilled during the execution of the scheduled tasks for this research, roles were allocated to each participant in the activity. Below is Table 7, which lists the proponents and their respective roles and responsibilities in fulfilling the research objectives.

Table 7

Table of Roles and Responsibilities

Member	Role	Responsibility
Jomar Leaño	Researcher & Developer	Research about Machine Learning for Multilabel Emotion Recognition
		Research about Composition of Complex Emotion
		Research about Emotion Wheel
		Determine Dataset for the Study
		Preprocessing Dataset
		Create the Code for the Models
		Train the Models using obtained Dataset
		Test the Models

		Determine Complex Emotion from Multilabel Emotion
		Evaluate according to predetermined criteria
Christian Stewart	Researcher & Developer	Research about Machine Learning for Multilabel Emotion Recognition
		Research about Composition of Complex Emotion
		Research about Emotion Wheel
		Determine Dataset for the Study
		Preprocessing Dataset
		Create the Code for the Models
		Train the Models using obtained Dataset
		Test the Models
		Determine Complex Emotion from Multilabel Emotion
		Evaluate according to predetermined criteria

4.9.3 Budget and Cost Management

Table 8 shows the list of expenses for conducting the study. The list contains items that the researchers used for this study, such as devices with an estimated cost for each type of device. Throughout the course of the study, all of the objects listed below are used. Things are core and generally applicable, and each type of item is unique to each researcher.

Table 8

Table of Expenses

Items	Cost
Laptop (M2 Macbook Air & Acer Nitro 5)	140,000.00
Conference Registration Fee	25,000.00
Miscellaneous (Food, Electric Bill, and etc.)	5,000.00
Total	**170,000.00**

4.10 Verification, Validation, and Testing

In this subsection, the methods for validation and testing of the model's performance in terms of determining the multilabel emotion, will be examined.

When the study's primary goal is achieved, it will be validated and verified to guarantee the study's integrity. This comprises the outcomes' accuracy and metric scores (such as precision, recall, and F1), as well as the procedures used for training and testing the data set. The procedures used to validate and verify the system are covered in this chapter's subsection.

The validation of the proposed model will be based on a comparison with the existing studies that have previously addressed the task of emotion classification. By benchmarking the performance of our Bi-LSTM model and BERT-CNN model against the results reported in this study, we can assess the effectiveness and improvement of our approach.

Table 9
Comparison of Similar Studies

Study Reference	Model	Experimental Results			
		Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Ashgar, M. et al. (2022)	Bi-LSTM	87.66	87.66	87.66	87.66
Abas, A. et al. (2021)	BERT-CNN	94.6	94.3	94.3	94

Table 9 shows the existing studies that serve as a reliable reference point, allowing us to validate the performance of our model and provide a meaningful evaluation of its accuracy, precision, recall, and F1-score.

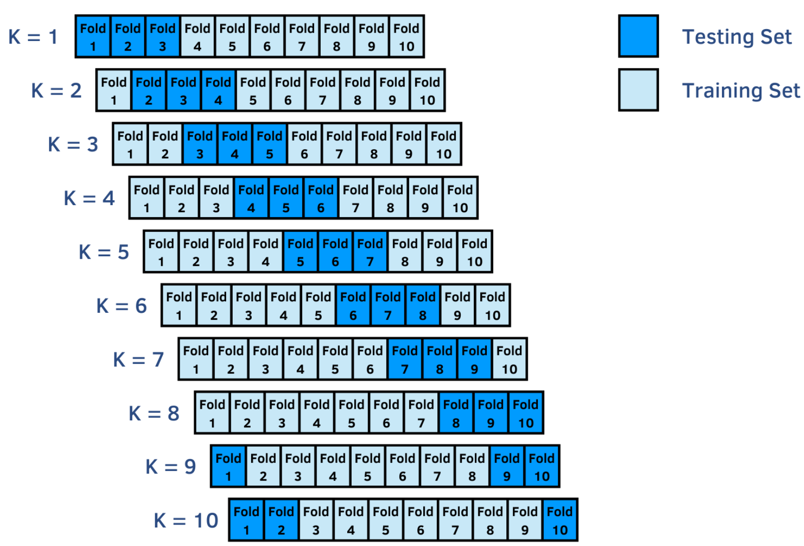


Figure 11. K-fold cross-validation method diagram (K = 10)

Performance measures are used for verification and validation, such as K-fold cross-validation, which divides the dataset into K subsets, each of which will serve as a testing set, and compares them to the other subsets in order to accurately assess the model's correctness. The number represented by the letter "K" represents the number of subsets to be used in the test. Tenfold cross-validation will be used in this investigation. In order to determine the average metrics of the model developed the accuracy, precision, recall, and f1 score of each test will then be averaged.

A confusion matrix will also be used. By comparing the projected class labels to the actual class labels, it will be easier to assess the model's accomplishments and shortcomings. This method is also essential for assessing models based on performance. A general confusion matrix structure is shown in Figure 12. Four cases TP, TN, FP, and FN can be created by combining predicted and actual values.

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

Figure 12. Confusion Matrix Diagram

The confusion matrix-derived standard evaluation metrics will be applied. Accuracy, precision, recall, and F1-score are metrics to be used. A measurement of accuracy is the proportion of the model's accurate predictions to all of its other forecasts. The accuracy is calculated using the equation below:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

The ratio of accurate positive predictions to all positive predictions made by the model is calculated using the precision metric. The following equation can be used to calculate precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall, on the other hand, evaluates the percentage of real positive cases that were correctly predicted out of all positive cases. It can be calculated using the formula below:

$$Recall = \frac{TP}{TP + FN}$$

Last but not least, the harmonic mean of precision and recall is where the f1-score measure comes from. It is a unitary measure that, when calculated using the formula: offers an overview of the tradeoff between precision and recall in the model's predictions.

$$F1 - score = 2 * \frac{precision * recall}{precision + recall}$$

In summary, for evaluation of the performance of the models in determining multilabel emotions through sequence labeling and sentence classification using textual data , these metrics will be assessed and compared for model selection.

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Date of Birth:	June 14, 2002
Age:	20
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Gender:	Male
Civil Status:	Single
Number of Children & Age:	None
Language Proficiency:	English, Filipino, Cebuano
Computer PMS & Software Skills:	Programming (C, C#, Java, React, Node, PHP, Laravel, JQuery, HTML, CSS, JS, Swift, Flutter, Express.js) Office Applications (Word, Excel, PowerPoint, OneNote) Design (Illustrator, Photoshop, Lightroom, Figma)

EDUCATIONAL BACKGROUND

1. **Education Level**

   (2020 - present)

   University of San Carlos - Talamban Campus

   Tertiary Level

(2018 - 2020)
De La Salle Andres Soriano Memorial College
Senior Secondary Level

(2014 - 2018)
De La Salle Andres Soriano Memorial College
Junior Secondary Level

(2008 - 2014)
De La Salle Andres Soriano Memorial College
Primary Level

2. **Certifications & Accreditations**
   2022 - 2023
   First Semester Dean's Lister
   School of Arts and Sciences

   2023
   Innovation Generation Season 3 Startup
   National Pitch, Top 50

   2022
   DICT Startup Challenge
   Regional Pitch, Top 6

   2021
   Getting Grounded on Analytics (Data Analytics)
   Development Academy of the Philippines

STRENGTHS, TRAITS, & SKILLS

1. Strong problem-solving skills and the ability to troubleshoot and debug code.
2. Good communication skills to collaborate with team members and effectively communicate technical concepts to non-technical stakeholders.
3. Proficiency in programming languages such as C, C#, PHP, and others.
4. Familiarity with software development methodologies such as Agile and Waterfall.
5. Persistent and logical thinker

CAREER OBJECTIVES

As a programmer, my career objective is to leverage my technical skills and passion for software development to contribute to the creation of innovative, high-quality software applications. I am committed to continuously learning and improving my programming abilities to stay up-to-date with emerging technologies and programming languages. My ultimate goal is to become a respected and influential figure in the programming community, known for my technical expertise, leadership abilities, and passion for software development. I am confident that my dedication, strong work ethic, and problem-solving skills make me a valuable asset to any organization that values innovation, quality, and collaboration.

REFERENCES

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Date of Birth:	April 14, 2002
Age:	22
Nationality:	Filipino
Gender:	Male
Civil Status:	Single
Number of Children & Age:	None
Language Proficiency:	English, Filipino, Cebuano
Computer PMS & Software Skills:	Programming (C, C#, Java, Python) Web Development (HTML, CSS, JS, React, Vue, Flutter) Office Applications (Word, Excel, PowerPoint, OneNote) Design (Illustrator, Photoshop, Lightroom, Figma)

EDUCATIONAL BACKGROUND

1. **Education Level**

   (2020 - present)
   Bachelor of Science in Computer Science
   Tertiary Level

   (2018 - 2020)
   Science, Technology, Engineering, Mathematics - Senior High School
   Senior Secondary Level

(2014 - 2018)
Basic Education Department - Junior High School
Junior Secondary Level

(2008 - 2014)
Maria Montessori International School
Primary Level

2. **Certifications & Accreditations**

   2022 - 2023
   First Semester Dean's Lister
   School of Arts and Sciences

   2022
   DICT Startup Challenge
   Regional Pitch, Top 35

   2021
   Computing in Python
   Development Academy of the Philippines

STRENGTHS, TRAITS, & SKILLS

1. Efficiency in Communication and Critical Analysis
2. Commitment to Development and Work Ethics, Conduct and Self-Discipline
3. High Attention to Detail and Passion for Technology
4. Flexibility and Adaptability in Computer Skills
5. Emotional Stability and Physical Endurance

CAREER OBJECTIVES

As a web developer with a passion for mobile app development, my career objective is to enhance my skills in Flutter and become proficient in creating seamless cross-platform applications that deliver an exceptional user experience. I aspire to work for a reputable company that values innovation and creativity, providing opportunities to work on challenging projects while exploring new frontiers in technology. In the long term, I aim to build a successful startup that leverages cutting-edge technologies to solve complex problems and make a meaningful impact on society. My ultimate goal is to establish a global presence by expanding my network, collaborating with talented individuals, and gaining diverse perspectives that fuel my growth as a professional and entrepreneur.

REFERENCES

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