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Multi-Label Emotion Classification Using Deep Learning on the Go-Emotions Dataset

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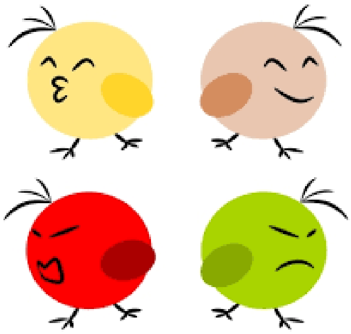
Abstract

This has increased the urgency to have proper emotion recognition structures that could recognize more than one co-occurring emotion due to the proliferation of textual information on social media generated by users. The purpose of this work is to create a deep learning model that will perform multi-label emotion classification with the use of Go-Emotions dataset. The overall aim is to identify five fundamental emotions, including anger, fear, joy, sadness, and surprise, provided in the text, and overcome such problems as linguistic noise, context ambiguity, and an imbalance in classes. Its methodology includes a lot of text preprocessing, that is, normalization, lemmatization, emoji management, and balancing classes and then the feature representation with a Text Vectorization and embedding layer. BiLSTM architecture is used to obtain long-range forward and backward contextual dependencies. The model is trained on binary cross-entropy loss with the Adam optimizer and tested on the basis of accuracy, precision, recall, and loss. It has been shown that the suggested BiLSTM model has an accuracy of 90.61, a precision of 90.41, and a recall of 92.25, and performs much better than traditional machine learning models and an existing mBERT+BiLSTM model. The results validate the hypothesis that a well-developed BiLSTM model with organized preprocessing offers a scalable and able performance in relation to multi-label emotion classification, which can be applied effectively to actual emotion-sensitive NLP tasks.

Keywords-Multi-label emotion classification, BiLSTM, Go-Emotions dataset, Deep learning, Natural Language Processing

1. Introduction

The fast development of the user-generated content on the online platforms has resulted in the enormous amount of written information sharing the human opinions, feelings, and emotions. This means that social media posts, online discussions, reviews and comments have abundant emotional content, which is an indicator of the psychological state and social relationships of the users. The automatic detection and interpretation of these emotions has also become an essential activity in Natural Language Processing (NLP), and is used in sentiment analysis, mental health analysis, human-computer interaction, recommendation systems, and social media analytics. Text emotion recognition extends beyond conventional sentiment analysis, which determines the text to be positive or negative, but instead detects subtle affective auras. Detection of emotions in text is not without several challenges as human language is complex. The expressions of emotion can be subtle, contextual and ambiguous and even a piece of text can have several emotions at the same time [1], [2], [3], [4], [5], [6]. Sarcasm, colloquialism, emojis, abbreviations and spelling variations also add to the task. Consequently, emotion recognition is often defined as a multi-label classification task, in which several emotional labels may be present in a textual input concurrently. To cope with the complexity, it is imperative to have strong datasets, efficient preprocessing schemes, and models that can learn long distance dependencies in the context [7], [8], [9], [10], [11].



Over the last few years, the availability of annotated datasets on a large scale has greatly contributed to the research in emotion analysis. Among them, the GoEmotions dataset has become one of the standard sources of information because of its taxonomy of emotions and the considerable number of labelled samples. This dataset consists of more than 200,000 Reddit comments annotated with a broad variety of emotional labels giving a rich and natural language representation of emotional expressions. With these datasets, it is possible to develop and test deep learning models that can be generalized to different linguistic styles and contexts. Deep learning models, especially the Recurrent Neural Networks (RNNs) and their variants, have shown great performance in the sequential text modeling tasks. The Long Short-Term Memory (LSTM) networks are perfectly adapted to deal with sequential dependencies and reduce the vanishing gradient problem that is inherent to conventional RNNs. Moreover, Bidirectional LSTM (BiLSTM) models improve contextual sensitivity in that sequences are used in both forward and backward directions and hence a model is able to learn the dependencies that can occur prior to or after a word in a sentence. Of particular significance here is that this bidirectional context is particularly relevant in emotion recognition, since the sense of an emotional signal is often conditional on other words [12], [13], [14], [15], [16].

Regardless of these improvements, important consideration of data preprocessing and class imbalance remains in order to successfully identify emotions. Noise in raw social media text is in the form of URLs, user mentions, emojis, long words, and irregular grammar. These factors can adversely affect the performance of the model unless there is systematic preprocessing. Also, emotional datasets are normally skewed in terms of label distributions and certain emotions occur much more often than others. These issues are addressed in this research by the means of text normalization, tokenization, lemmatization, and class-balancing techniques to establish reliable and generalizable models. The proposed research is centered on constructing a structured deep learning structure to classify multi-label emotions using the selected core emotions-anger, fear, joy, sadness and surprise- using the GoEmotions dataset. These are the most common emotions that are researched in affective computing and are the basic emotional states that are important to not only the psychological research but also the actual applications. The research combines the extensive preprocessing methods and a BiLSTM-based architecture to successfully extract semantic and contextual information in text. This is made possible by the application of embedding layers, regularization methods, and the correct loss functions that guarantee that the model can learn meaningful representations of emotions in addition to minimizing overfitting.

The major goal of the study is to develop and test an effective approach to identifying multiple emotions based on textual information with the help of deep learning. Through a blend of the high quality annotated data, systematic preprocessing as well as a sophisticated neural network architecture, the study will make contributions to the expanding literature of emotion-sensitive NLP systems. The suggested method will be a versatile and scalable one, which can be applied to a wide range of practical uses: Section II of this paper will be a review of the literature in emotion recognition and deep-learning-based text classification. Section III explains the research methodology, the data collection, the preprocessing, and the model design. Section IV shows the experimental analysis and discussion and Section V provides a conclusion of the study with main observations and suggestions to the future research.

2. Literature Review

Kaur & Sharma, 2023.E-commerce, platforms, news portals, search engines, and news portals, and creating huge flows of data every second. The analysis of this data helps the company to determine how people feel about different products, brands and services to make wise decisions. The proposed study is aimed at developing a consumer review summarization model based on Natural language Processing (NLP) and Long Short-Term Memory (LSTM) to summarize reviews and bring forth meaningful insights into the consumer behaviour and preferences. A hybrid framework of sentiment analysis is proposed and includes preprocessing, feature extracting, and sentiment classification. The preprocessing phase eliminates irrelevant items in the text being reviewed and feature extraction fuses the review-based and aspect-based features to form a unique hybrid feature vector of each entry. A sentiment classification is provided in the form of an LSTM deep learning model. The performance at experimental evaluation on three research datasets is high, the average precision of evaluation is 94.46, recall is 91.63, and F1-score is 92.81 [17].

Shi 2023 et al. Opinion recognition and classification of opinion on text are quite useful in enhancing user comprehension and online services but the issue of multi-label classification in a short time is still a challenge. To minimize this drawback, an extended version of Multi-label K-Nearest Neighbors (MLkNN) algorithm is proposed, which takes into consideration not only the features of separate sentences, but also those of the neighboring sentences and entire tweets. Adjusted method enables correction of multi-label emotion predictions iteratively to achieve higher rates of classification and accuracy of short texts on Twitter. Comparison of three experimental groups on a Twitter corpus between the standard MLkNN, sample-based MLkNN (S-MLkNN), and label-based MLkNN (L-MLkNN). Results show that the enhanced MLkNN has a considerable effect in improving emotion classification performance with K = 8 and 0.7 yielding the highest overall results with L-MLkNN recording the highest recall at 0.8019. It is suggested that future studies should trade-off model efficiency with sufficient coverage of different sentiment situations [18].

Chango 2022 et al. Digital and context-aware technologies are becoming more important to the work of smart learning environments through the advancement of educational experiences that

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produce vast amounts of multimodal student data under all sources. A combination of audio, video, electrodermal activity, eye-tracking, user logs, click-stream behaviour and learning artifacts, and natural human indicators, including gestures, gaze, speech, and writing, are valuable opportunities to learn more about the learning processes and can provide timely interventions. To apply this information effectively, there should be the appropriate application of data fusion techniques that can be used to combine these different modalities in multimodal learning analytics (MLA). In this survey, the author introduces the contribution of data fusion to learning analytics (LA) and educational data mining (EDM) and describes the ways in which fusion methods can assist in creating smart learning environments. It examines major publications, which often combine various types of educational data, and leading fusion strategies and determines unresolved issues, emerging trends, and challenges. The research paper also suggests the significance of strong data fusion processes in enhancing research and practice in MLA and smart education systems [19].

Wang 2021 et al.The medical data technology has developed tremendously in the last twenty years, and has helped in the analysis of diseases significantly, but it is not possible to early diagnose emotional and mental disorders. The studies are interested in remedying this problem through a hybrid multi-feature classifier based on AI to classify emotional states as positive or negative. The methodology uses ensemble learning to identify the best features among the sentiments on the social media available, which improves accuracy of classification. The dataset will be separated into training and testing data to create and test the most efficient predictive model. Experiments have been done on the MovieLens class label set, and it is shown that the ensemble learning approach provides the best classification performance, through the maximization of feature separation. The findings indicate the enhanced efficiency of the suggested system in the correct recognition of the initial signs of emotional distress, which can potentially bring positive results to the clinical diagnosis and mental health monitoring based on the sophisticated data mining and machine learning algorithms [20].

Shin 2021 et al. Human communication does not necessarily just limit itself to the aspect of body language but also involves high level language and written text that expresses elaborate thought processes. Textual information, which is read every day, includes concealed patterns on the cognitive processes and feelings of the author. Conventional text analysis based on counting words can usually have no meaning. To counter this a nonlinear emotion system founded on emotional weighting was suggested in order to improve document diversity and feature convergence. This method uses nonlinear functions in addition to the available training and learning methods to provide the right feature weights. The confusion matrix, area under the receiver operating characteristic curve (AUC), and F1-score are the evaluation metrics that are used. A different error measure was created to determine emotions more precisely. The model had an accuracy of 0.9447 and a max AUC of 0.9845, which is as good as TF-IDF based methodology. Such findings suggest that the model is effective in the ability to capture subtle emotional material in text to enhance emotion analysis [21].

Table 1. Literature Summary

Authors/Year	Methodology	Research gap	Findings

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Series/2021[22]	Data mining methods applied in e-commerce for emotion-oriented systems.	Limited integration of intelligent emotion recognition in e-commerce systems.	Intelligent emotion recognition advances support emotion-based e-commerce development.
Saxena/2020[23]	Reviewed facial, physiological, speech, and text-based emotion recognition methods.	Lack of comprehensive review covering all emotion recognition models recently.	Particle Swarm Optimization with Biogeography optimization achieved highest accuracy.
Ahuja/2019[24]	Preprocessing, feature extraction (TF-IDF, N-Gram), six classifiers evaluated.	Limited comparative analysis of TF-IDF and N-Gram on tweets.	TF-IDF word-level features outperform N-Gram by 3-4% accuracy.
Angelina/2019[25]	Emotion detection on Twitter using SVM LibLinear model achieving accuracy.	Limited exploration of actionable recommendations based on detected user emotions.	Achieved 98% accuracy; extracted emotion-based action rules for users.
Kumar/2017[26]	Used supervised and unsupervised machine learning for Twitter sentiment analysis.	Challenges in analyzing large, unstructured sentiment data efficiently remain.	Unsupervised approach achieved 80.68% accuracy; supervised methods varied performance.

3. Research Methodology

The research of this paper is based on a multi-label emotion classification deep learning pipeline. First, a huge size of textual data, annotated by humans, is chosen to make sure that there is diversity and dependability in the expression of emotions. Recent categories of emotion are recognized and the information is preprocessed in a systematic way to clean up the text, normalize and tokenize and lemmatize it to eliminate noise and enhance semantic consistency. The imbalance in classes is controlled by means of proper sampling and weighting. A numericization and encoding mechanism is used to convert the processed text into numerical representations. BiLSTM network is then developed to learn contextual information of both previous and consecutive words in a sentence. Appropriate optimization and loss functions and regularization techniques are included to aid in the stable learning and generalization within a multi-label classification context and Machine learning too is used in classification.

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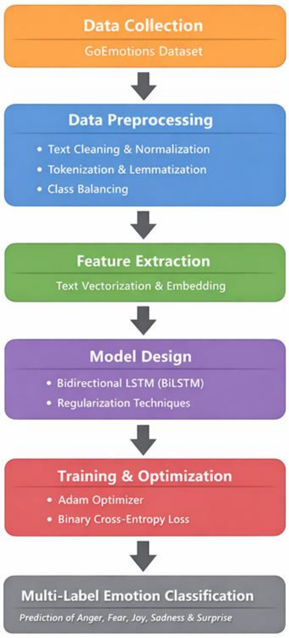

Fig.1 Proposed Flowchart

A. Data Collection

The GoEmotions database, which is used in emotion recognition studies, contains 2112225 tagged textual samples that were obtained on the Reddit site and which cover a wide variety of human emotions in natural language. The data is stored in the form of a record that contains the ID, author, subreddit, link ID, parent ID, and the time when it was created, in UTC format. In order to achieve thorough annotation, every text snippet was scored by several human annotators, and a binary column (example very unclear) identifies the snippets that can be considered hard to read. The dataset will have 37 columns (29 integer columns) that will describe various emotion labels, including admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise and a neutral column. The metadata columns in the dataset also contain the contextual information of each text and allow the further analysis of the distribution of emotion within the various subreddits and authors. The GoEmotions dataset, with a total memory footprint of over 58 MB, is one of the largest publicly available corpora of fine-grained emotion detection, suitable both to supervised machine learning and deep learning models to make predictions in multiple emotions at the same time, and to enable more advanced studies in sentiment analysis and affective computing.

B. Data Preprocessing

Preprocessing the Go Emotions data was aimed at preparing the text data to be classified in terms of multiple labels corresponding to emotions. In the first experiment, there were five selected target emotion columns-anger, fear, joy, sadness, and surprise- and these were paired with the adequate text attached and rows with no positive labels amongst these emotions were eliminated so that significant training samples could be yielded. The uncoded text was heavily purged, with contractions being expanded, URLs and user mentions being removed, and emojis being replaced by text-based descriptions in order to preserve emotional context. The hashtags got simplified

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keeping the text part, and the repetition of the letters in words (l.o.v.e) became standard. All alphanumeric characters were filtered and punctuation was retained and all the text was lowercased to ensure uniformity. The NLTK WordNetLemmatizer was used to tokenize and light lemmatize the data to eliminate noise in variable forms of the word. Short and numeric-only tokens were abandoned to improve the quality of the signal. A Textvectorization layer was then used to clean the text and the maximum vocabulary used was 50,000 tokens and sequence length was set at 120. Lastly, stratified train-test split (80-20) was done, and inverse-frequency sample weighting calculated to deal with class imbalance and produce datasets that were efficient to train using batch processing and prefetching to optimize deep learning workflows.

C. Modeling

- **Deep learning Model:** The deep learning model to be used in the multi-label emotion classification task was a bidirectional Long Short-Term Memory (BiLSTM) network, which was developed to capture the dependencies of the textual data in context. The input layer receives sequences of token sequences of integer-encoded text the text has been cleaned, then through an embedding layer with 150 dimensions to produce dense vector representations of words. The application of a Spatial Dropout1D layer was to ensure overfitting was avoided, where the dimensions of the embedding were dropped as needed randomly. The essence of the model is Bidirectional LSTM of 128 units, which provides the network with an opportunity to learn patterns both in the forward and the backward direction and dropout and recurrent dropout are regularized at 0.3. The LSTM output is then connected to a fully connected dense neural network of 128 neurons and ReLU activation, and there are extra dropout layers to minimize further overfitting. The last output layer applies a sigmoid activation to estimate the likelihood of every of the five classes of emotions separately, and thus it is applicable in multi-label classification. The model was trained using the Adam optimizer, binary cross-entropy loss function and measures of evaluation were accuracy, precision and recall. This architecture provides a good trade-off between sequence modeling and regularization, and allows to learn subtly emotional information in textual data.
- **Machine learning Models**
  - ➢ **Logistic Regression:** The Logistic Regression model is also applied with One-vs-Rest strategy in order to deal with multi-labeled emotion classification. The inputs are TF-IDF features and the model learns a binary classifier of every emotion independently. The LBFGS optimizer and more iterations tend to ensure a consistent convergence of training.
  - ➢ **Linear Support Vector Machine:** Linear SVM model takes a One-vs-Rest classification model that allows each emotion label its own linear decision boundary. The model is based on the TF-IDF feature vectors, which aim at achieving maximum class separation margins, and thus, are applicable to high-dimensional sparse text representations which are common in NLP tasks.
  - ➢ **XGBoost:** XGBoost model is applied in the One-vs-Rest methodology in order to enable multi-label classification. It models non-linear relationships in TF-IDF features using gradient-boosted decision trees, and has controlled depth, learning rate and subsampling to reduce overfitting and to enhance learning stability.

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4. Result & Discussion

A. Performance Evaluation of Proposed Hybrid Deep Learning Model

Table 2. Performance Evaluation Of Deep Learning Model

Model	Accuracy	Loss	Precision	Recall
BiLSTM (Proposed)	90.61	0.0715	90.41	92.25

The suggested BiLSTM model shows high results having an accuracy of 90.61 and a low loss of 0.0715, which proves to be learning successfully. The precision (90.41) and recall (92.25) are high, which proves reliable multi-label emotion detection with a minimum number of false predictions.

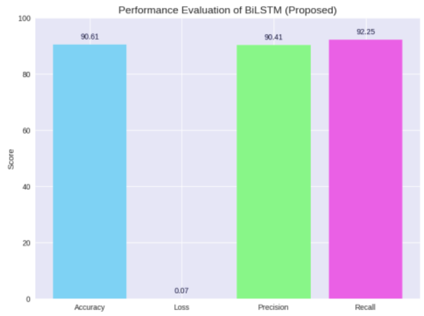

Fig.2 Performance Evaluation of Proposed Hybrid Deep learning Model

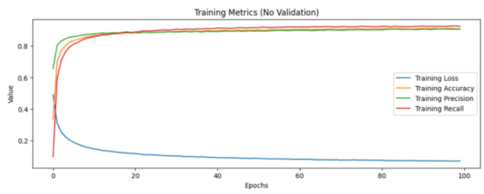

Fig.3 Training Metrics Graph of BiLSTM Model

The loss level becomes lower and more rapidly, whereas accuracy, precision, and recall increase rapidly and then level-off showing that the model is learning successfully, though it has to be validated to prevent overfitting.

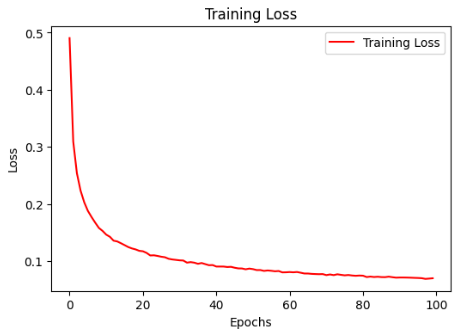

Fig.4 Training Loss

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Loss measures model error. It declines gradually and this indicates that the model is learning and is becoming more and more accurate in its predictions.

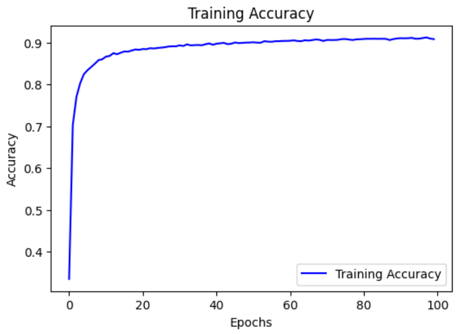

Fig.5 Training Accuracy

The accuracy increases rapidly, and then levels off. It indicates the average frequency of correct predictions of the model on training epochs.

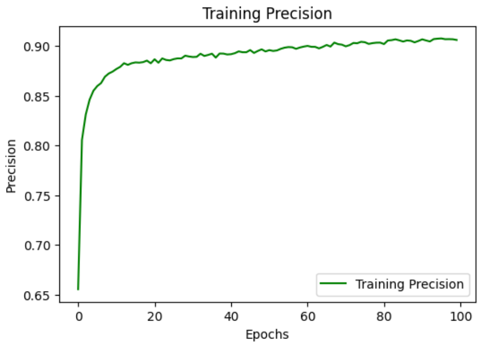

Fig.6 Training Precision

Precision rises shortly, becomes close to 0.90. It demonstrates the ability of the model to detect false alarms.

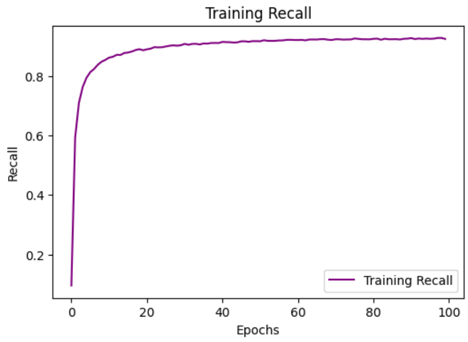

Fig.7 Training Recall

The rate of recall levels off. It shows how the model is capable of identifying all the positive cases that are relevant.

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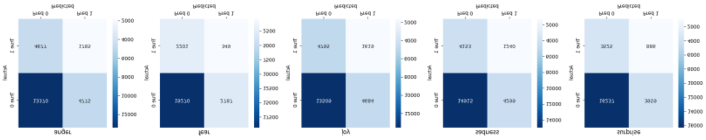

Fig.8 Confusion matrix ofBiLSTM

The individual confusion matrices indicate the level of effectiveness of the model in classifying emotions. There are true positives and negatives which differ depending on emotions. Anger, joy and sadness are more misclassified as compared to fear and surprise. Precision and recall are different, which means that the model finds it more difficult to deal with certain emotions. These matrices aid in measuring the accuracy of classification and errors.

B. Performance Evaluation Machine learning Models

Table 3. Performance Evaluation of Machine learning Models

Models	Accuracy	Precision	Recall	F1 Score	Loss
Logistic Regression	50.3	91	63	74	0.11
Linear SVM	62.36	83	73	78	0.108
XG boost	54.42	88	67	76	0.111

The analysis of performance indicates a deviation between the machine learning models. The lowest accuracy (50.3) is achieved by Logistic Regression despite its high accuracy as it makes accurate positive predictions but poor ability to classify in general. Linear SVM provides the most balanced results with the highest accuracy (62.36%), recall (73%), and F1-score (78%), which indicates its greater generalization and stability. XGBoost has an average precision (88%), reduced accuracy, and recall, indicating that it is sensitive to the distribution of classes. The value of losses in the models is comparable which means that they converge similarly. All in all, Linear SVM is better than the rest of the models as it is more precise, has a higher recall and has a higher overall accuracy.

Fig. 9 Performance Evaluation Machine learning Models

C. Comparative Analysis

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Table 4. Comparative Analysis between Existing & Proposed Work

Models	Accuracy	
mBERT+BiLSTM	57	[27]
Proposed BiLSTM	90.61	--

The comparison analysis shows clearly the excellence of the suggested BiLSTM model with the current mBERT+BiLSTM method. Although the mBERT+BiLSTM model has a low accuracy of 57 it is still significantly better than the proposed BiLSTM model which has a high accuracy of 90.61. The given enhancement is explained by the optimized architecture and learning of the proposed model towards the task-specific features, which minimizes the unwarranted complexity and overfitting that is caused by mBERTembeddings. The suggested BiLSTM is able to properly represent contextual dependencies to the dataset, which results in an improved generalization and quicker convergence, as well as more precise classification results as compared to the current hybrid model.

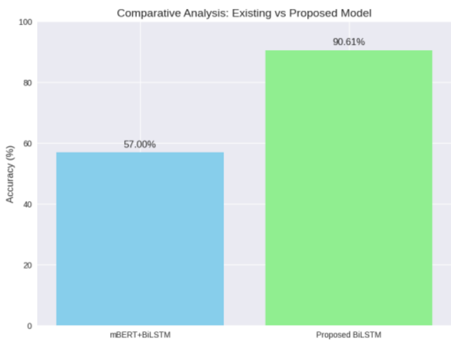

Fig.10 Comparative Analysis

5. Conclusion

In this paper, a deep learning solution to multi-label emotion classification on GoEmotions data set was proposed, and it aimed at identifying five fundamental emotions, namely anger, fear, joy, sadness and surprise. The systematic preprocessing of texts and the well-thought BiLSTM structure allowed the proposed framework to resolve the main issues associated with contextual ambiguity, text noise, and imbalance among classes in social media. The experimental findings showed that the proposed BiLSTM model has high performance with high accuracy, precision and recall indicating that it is able to understand subtle emotional patterns in text. Compared to the classical machine learning model regressions like Logistic Regression, Linear SVM, and XGBoost, the deep learning model demonstrated visible superiority in aggregate classification interests. More so, the comparative analysis to an existing mBERT+BiLSTM model emphasized that a task-specific and optimized BiLSTM architecture could perform well than a more complicated hybrid model due to a minimal unnecessary computational overhead and overfitting. The results confirm the appropriateness of BiLSTM networks to emotion-aware NLP tasks involving contextual understanding as a key factor. In general, the study has added a strong and scalable framework in recognizing multi-labeled emotions, which can be used in sentiment-based analytics, social media, mental health, and emotionally intelligent human-computer relationship systems. Further development of work could include the inclusion of new categories of emotion, architectures based on transformers, and generalization to cross domains to improve performance further.

Author Contributions
All authors contributed equally to the design, analysis, and writing of this study and have approved the submitted version.

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Conflicts of Interest
The authors declare that there are no conflicts of interest regarding the publication of this paper.

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