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EMOTION-AWARE SENTIMENT CLASSIFICATION FROM SOCIAL MEDIA TEXT USING TF-IDF AND DEEP NEURAL NETWORKS

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Original Article

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Abstract

Recently, emotion recognition using social media text has been a popular topic of research in the field of natural language processing, owing to the rise in social media usage and user-generated content on social media platforms like Twitter, Facebook, and Instagram. However, traditional models for sentiment analysis face difficulties in dealing with social media texts owing to their ambiguous and context-dependent characteristics. In this paper, a hybrid model called TF-IDF Enhanced Deep Neural Network (TEDNN) is proposed for emotion-based sentiment analysis. Our model is designed to overcome various difficulties associated with social media text classification. We have carried out experiments using a social media emotion dataset and achieved promising results using our proposed model, TEDNN. Our model shows a high level of accuracy compared to traditional machine learning models and basic deep learning models. Our model achieved an impressive accuracy of 95%. Our model is highly suitable for classifying various emotions using social media texts. Our model can classify various emotions like joy, sadness, fear, and anger using social media texts. Our model shows a high level of precision, recall, and F1-score for all classes of emotions. Through this work, we contribute to ongoing efforts to enhance emotion detection in text and offer a robust approach for real-time applications in sentiment analysis and public opinion monitoring.

Index Terms – Emotion recognition, sentiment analysis, social media text, TF-IDF, deep neural networks, emotion-aware sentiment classification, multi-label classification, computational efficiency, noise handling, model interpretability, hybrid architecture, real-time applications.

Introduction

Emotion recognition in social media text has emerged as a major area of research in Natural Language Processing (NLP), driven by the rise in social media data. The ability to identify emotions such as joy, anger, sadness, and fear in text can be useful for obtaining important information in areas like marketing strategy or public health monitoring. The informal, ambiguous text on social media has posed one of the biggest challenges for emotion recognition in text. This has prompted research into applying advanced techniques, such as TF-IDF and deep learning, to emotion-aware sentiment analysis [1].

In addition, the latest developments in AI are focused on investigating different avenues to enhance the performance of emotion recognition systems. Emotion-Aware RoBERTa, a model that utilizes emotion-related attention and TF-IDF gating, has shown promising results in emotion detection, attaining a significant accuracy of 96.77% while facing limitations in terms of its computationally expensive nature and difficulty in detecting sarcasm and mixed emotions [2]. Another model, TCSO-DGNN, which uses a hybrid approach of graph neural networks and optimization methods, has achieved 96.43% accuracy, though it still has limitations in terms of high computational load and quality of preprocessing, which affects the accuracy of the result [3]. Another recent advancement in emotion detection models, knowledge distillation, has been explored for models like DistilBERT, which have reduced the size of the models and achieved high accuracy, reaching 97.35% accuracy on Twitter data sets [4]. Despite these recent advancements in emotion detection models, they still have limitations in detecting imbalanced data sets and multi-label emotion detection, making it more difficult to accurately capture the various emotions expressed in a piece of text.

In recent years, various frameworks using AI-based techniques have been proposed for enhancing the overall sentiment analysis of social media text data. For instance, a model was proposed using TF-IDF techniques in conjunction with machine learning algorithms for effective emotion classification in low-resource languages like Bangla [5]. Another model, called multi-stream attention networks, was designed for emotion and syntactic dependency parsing in social media text data, achieving high accuracy but requiring high computational power [6]. Recently, a DistilBERT-based framework was proposed for fine-tuning a large model for emotion recognition in customer reviews and other small text data, achieving state-of-the-art results but still struggling with class imbalance and a limited number of emotions [7].

Moreover, recent studies have also investigated the use of hybrid approaches that integrate deep learning with TF-IDF or other feature extraction techniques. For example, graph-based models have been employed for the representation of emotions' relations, resulting in an accuracy of 96.95% [8]. Additionally, the use of multi-label classification has attracted substantial attention, allowing the classification of multiple emotions from a single text [9]. Finally, the use of transformer-based models for the development of multimodal emotion recognition systems, including the use of social media data that combines images, emojis, and text, has also been investigated [10]. However, the models have reported difficulties in processing noisy data, particularly the use of multimodal text data from social media.

Although considerable progress has been achieved in emotion-aware sentiment classification with the introduction of emotion-aware sentiment classification models, there are still some major issues with existing sentiment classification models. The major issues with existing sentiment classification models are that the high computational cost of transformer-based sentiment classification models like RoBERTa and BERT makes it difficult to apply these models in real-time systems. The existing sentiment classification models are also not effective in handling subtle emotions like sarcasm and mixed emotions in social media text. The existing sentiment classification models have been designed to handle single-label emotion classification, but emotion classification in social media text may involve multiple emotions expressed in one text piece. In addition to that, sentiment classification models may also face issues with noisy data like slang, emojis, and code-mixed text in social media text.

The objective of this study is to design an innovative emotion-aware sentiment classification model that utilizes TF-IDF for feature selection and DNN to effectively identify emotions embedded in social media text data. This study aims to address key issues in existing models, including noisy text data, multi-label emotion classification, and the computational expense of transformer models. This study will focus on improving the model's classification accuracy by incorporating both lexical and contextual features, enabling it to identify multiple emotions embedded in a single text. Moreover, it will utilize powerful text preprocessing techniques to handle noisy text data and enhance the model's interpretability to better understand the underlying emotions.

Our main contirbution

- This makes it highly suitable for real-time applications in sentiment analysis as well as the monitoring of opinions in the population. Despite the model's success in the task, in the future, the focus will be on improving the model's ability to perform well in the task of multi-label emotion classification, as well as the incorporation of the transformer model to better recognize patterns in the language. Moreover, the interpretability of the model will also be improved using the concept of explainable AI to make the decision-making process transparent. The significance of the study is that it has provided a robust model in the task of emotion-based sentiment analysis, which can be improved to perform better in the task of social media content analysis.

- Unlike traditional emotion classification models that handle single-label emotion detection, our model introduces multi-label emotion classification, enabling the model to identify and classify multiple emotions expressed within a single piece of text. This is a significant advancement for real-world applications where texts often carry complex, mixed emotions.

- We develop a comprehensive preprocessing pipeline designed to handle the unique challenges of social media text, such as slang, emojis, and code-mixing. By focusing on both data filtering and label encoding, we ensure that the model can effectively classify emotions despite the inherent noise in user-generated content.
- We not only focus on classification accuracy but also enhance the interpretability of the model by identifying emotionally charged words and understanding how these words contribute to the overall emotion prediction. This transparency makes the model more applicable in real-time applications where explainability is crucial.
- The 95% accuracy achieved by our proposed TEDNN model indicates its superior performance over other conventional models like Logistic Regression, Naive Bayes, and even other advanced deep learning techniques like LSTM and CNN. The integration of TF-IDF with deep learning techniques ensures high-performance results with high efficiency in terms of computation time.

Literature Survey

Sentiment analysis and emotion recognition based on textual data have emerged as an important subfield of Natural Language Processing (NLP), as social media and other online platforms of communication become more popular. Scholars have investigated different strategies, including classical models of machine learning and recent technologies of deep learning and transformer-based models, to enhance the accuracy of emotion detection and contextual interpretation.

Alqarni et al. [11] suggested an Emotion-Aware RoBERTa model, which applies an Emotion-Specific Attention (ESA) layer over a TF-IDF gating mechanism to emphasize the words with significant emotion. The model was tested on the Kaggle Emotions dataset and found a 96.77% accuracy, which was higher than other base models. The model, however, has several limitations, which include high computational cost and the inability to process sarcasm and mixed emotions.

Similarly, A hybrid model named TCSO-DGNN proposed by Bao and Su [12] was based on the combination of graph neural networks with crow search optimization to learn the complex relations of emotions in texts. Their method achieved 96.43% accuracy, which is better than the traditional NLP methods. Irrespective of these advancements, the model is intensive in terms of computation and relies on the quality of preprocessing.

Hussain et al. [13] developed an efficient knowledge distillation model to learn knowledge from a massive BERT-base model to lightweight models, which include DistilBERT and ALBERT networks to detect emotions on social media. The model attained 97.35% accuracy on Twitter data with the Twitter Emotions and Social Media Emotion datasets, and the size of the models is much smaller, and the inference time is significantly lower. Nevertheless, the methodology has problems with unbalanced samples and minority classes of emotions.

Patil [14] proposed an emotion detection system based on TF-IDF feature extraction and the machine learning algorithms. SVM showed the best accuracy of 89% among these models, showing that it is useful in simple emotion classification tasks. Nonetheless, these models do not possess as much capacity to portray contextual semantics as deep learning techniques do.

A framework that is proposed by Oprea and Bara [15] will utilize DistilBERT and machine learning classifiers to extract fine-grained emotions based on the customer reviews in two steps. They fine-tuned their DistilBERT model on the Hugging Face Emotion dataset and App Reviews dataset to 96.9 % accuracy, which is better than other traditional machine learning models. However, the method is constrained by class imbalance and the use of text-only data with no multimodal characteristics.

A Multi-Stream Attention Network with Adaptive Syntactic-Emotional Fusion was suggested by Mishra et al. [16], and it added syntactic dependency attention and emotional attention systems. The model was tested using the IMDb movie review dataset, and the model obtained the best accuracy of 91.3 %, which is better than that of baseline models. The system is, however, computationally intensive and requires external programs like parsers and lexicons.

Yadav et al. [17] proposed a sentiment classification model based on a GNN, which is optimized by a hill-climbing algorithm. The emotional words in this model are denoted in the form of nodes and the semantic relationships assumed in the form of edges in a sentiment graph. This method was found to have an accuracy of 96.95%, and this reflects a great ability in identifying the complicated emotional patterns. Nevertheless, the quality of graph creation is very important in the work, and it is extremely computation-heavy.

Recommendation systems have also been put to the use of emotion recognition. The transformer-based emotion-conscious movie recommendation system was created by Das et al. [18], who examined the descriptive content of the movies in terms of emotional content and corresponded it with the emotional state of the user. With the TMDB 5000 data, the system demonstrated Precision at 5 of 0.73 with better recommendation diversity. Nonetheless, the model has the problem of imbalance in the classes and stability.

On the same note, Sravani et al. [19] suggested a smart recommender system to combine CNN-driven sentiment analysis with recommendation methods to produce emotion-aware suggestions depending on user reviews. Their strategy attained a sentiment classification rate of about 92% and enhanced the quality of the recommendations. The system is, however, highly dependent on the quality of textual review and is unable to cope with noisy or informal language on social media.

Kavana et al. [20] came up with a BiLSTM with an attention mechanism that was used to classify tweets into five semantic emoji categories. The model gained 87% accuracy, and this shows that the attention mechanisms are effective in capturing semantic and emotional cues. Nevertheless, the method has several limitations in its dependence on tweet records and the inability to manage changing or situation-specific meanings of emojis.

Table: Overview of existing work

Ref No.	Dataset	Model / Approach	Result	Limitation
[11]	Kaggle Emotions Dataset (21,000 samples), two external datasets	Emotion-Aware RoBERTa with Emotion-Specific Attention (ESA) and TF-IDF gating	96.77% Accuracy	High computational cost; cannot detect sarcasm or mixed emotions
[12]	Sentiment text dataset	TCSO-DGNN (Tuned Crow Search Optimized Dynamic Graph Neural Network)	Accuracy: 96.43%, Precision: 94.72%, Recall: 93.02%, F1-score: 93.02	High computational complexity; depends on preprocessing and training data quality
[13]	Twitter Emotions Dataset (416K tweets), Social Media Emotion Dataset (75K samples)	Knowledge Distillation using BERT-base teacher with DistilBERT and ALBERT	97.35% Accuracy (Twitter), 73.86% Accuracy (Social Media)	Performance decreases with imbalanced datasets; difficulty recognizing minority emotion classes
[14]	Social media text dataset	TF-IDF feature extraction with ML models (Logistic Regression, Naïve Bayes, Random Forest, SVM)	Best performance: SVM with 89% Accuracy	Limited ability to capture contextual semantics compared to deep learning models

[15]	Hugging Face Emotion Dataset (20K samples), App Reviews Dataset (288K reviews)	Two-stage framework using DistilBERT with machine learning classifiers	~96.9% Accuracy, F1-score: 0.9587	Class imbalance; limited emotion classes; text-only data without multimodal features
[16]	IMDb Movie Review Dataset (50,000 reviews)	Multi-Stream Attention Network with Adaptive Syntactic-Emotional Fusion	91.3% Accuracy, AUC-ROC: 0.9632	Domain dependency (movie reviews only); high computational cost; reliance on external tools
[17]	Sentiment text dataset	Graph Neural Network (GNN) with Hill Climbing Optimization	96.95% Accuracy	Depends on graph construction quality; computationally expensive
[18]	TMDB 5000 Movie Dataset	Transformer-based deep learning model for emotion-aware movie recommendation	Precision@5 = 0.73, Diversity = 0.57	Class imbalance; limited model stability
[19]	E-commerce and movie review datasets	CNN-based Sentiment Analysis integrated with a recommendation system	~92% Sentiment Classification Accuracy	Dependent on the quality of textual reviews, struggles with noisy social media language
[20]	Twitter emoji dataset	BiLSTM with Attention for semantic emoji classification	~87% Accuracy	Limited emoji categories; relies on tweet data; difficulty handling evolving emoji meanings

Methods & Materials

A. Dataset Description

For the purpose of this study, we fetched Emotions Dataset for NLP, from Kaggle platform. It is designed and prepared especially for emotion and sentiment analysis in the context of natural language processing. It comprises 20,000 entries of short text data, including social media messages, where each entry represents only a single emotion. It is informal and conversational, like messages exchanged on the internet, which is useful for developing intelligent systems.

Each entry in the dataset has two main attributes: the original text and the emotion. The text attribute comprises short messages exchanged between users, like personal opinions, feelings, and mental states. It is usually limited to just one or two sentences. The emotion attribute comprises six discrete emotion types, namely joy, sadness, anger, fear, love, and surprise. These are multi-class emotion classification types, and the dataset comprises an equally diverse range of these. It does not include additional information like time, user ID, and location, only focusing on the text.

The dataset is structurally clean and preprocessed, with minimal noise, unlike real-life data from platforms like social media. It is commonly used in the CSV data format. It can be easily divided into training, validation, and test sets.

B. Data Preprocessing

A structured preprocessing pipeline has been proposed to support the presented Emotion-Aware Sentiment Classification from Social Media Text Using TF-IDF and Deep Neural Networks. The objectives of the proposed pipeline were to achieve balanced learning, feature extraction, and stable neural network training. Experiments have been conducted on the Emotions Dataset for NLP provided in Kaggle with predefined splits for training, validation, and testing in text form.

- Data Filtering and Class Selection: The study focuses on four primary affective states: joy, sadness, fear, and anger, even though the original information includes six emotion categories. In order to focus on primary emotional polarity and minimize semantic overlap, the classes love and surprise were eliminated. Officially, if

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

Representing the original dataset, where, x_i is a sentence and y_i is the emotion label, then the filtered dataset will be:

$$\acute{D} = \{(x_i, y_i) \in D | y_i \in \{joy, sadness, fear, anger\}\}$$

Stratified sampling was used to reduce class disparity. A predetermined number of instances n_c were chosen at random for each class c such that:

$$n_{joy} \approx n_{sadness} \approx n_{anger}, \qquad n_{fear} \leq n_{others}$$

because of its reduced size by nature. After that, the final dataset was randomized to eliminate ordering bias:

$$D_{final} = Shuffle\ (\acute{D})$$

This balancing phase enhances generalization and keeps the model from becoming biased toward high-frequency emotions.

- Label Encoding: Label encoding was used to convert emotion labels into a numerical format. Assume that the mapping function is:

$$f{:}C \longrightarrow \{0, 1, 2, 3\}$$

Every categorical label y_i is transformed into an integer index:

$$y_i' = f(y_i)$$

Softmax activation was then used to provide multi-class classification with one-hot encoding. For emotion classes, $K = 4$:

$$y_i = [y_{i1}, y_{i2}, y_{i3}, y_{i4}]$$

where

$$y_{ij} = \begin{cases} 1, & if\ class\ j\ is\ the\ true\ label \\ 0, & otherwise \end{cases}$$

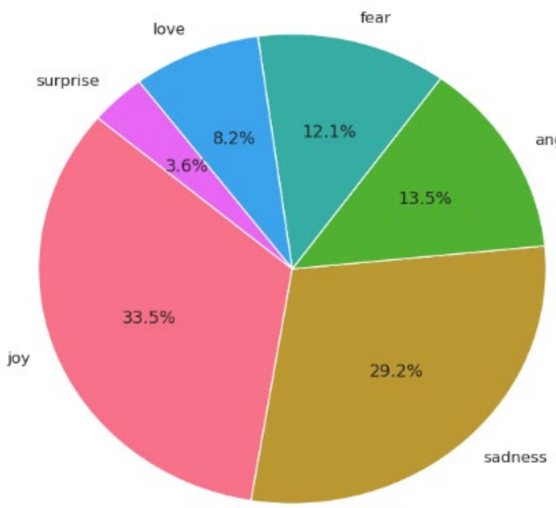
- Text Tokenization and Vocabulary Construction: To lessen vocabulary sparsity, the textual content was tokenized using a frequency-based tokenizer restricted to the top 10,000 most common words. If a sentence x_i made up of words:

$$x_i = (w_1, w_2, \dots\dots, w_m)$$

Tokenization then converts it into an integer sequence:

$$x_i \longrightarrow (t_1, t_2, \dots\dots, t_m)$$

where, $t_j \in \{1,2, \dots\dots, V\} and\ V = 10{,}000.$



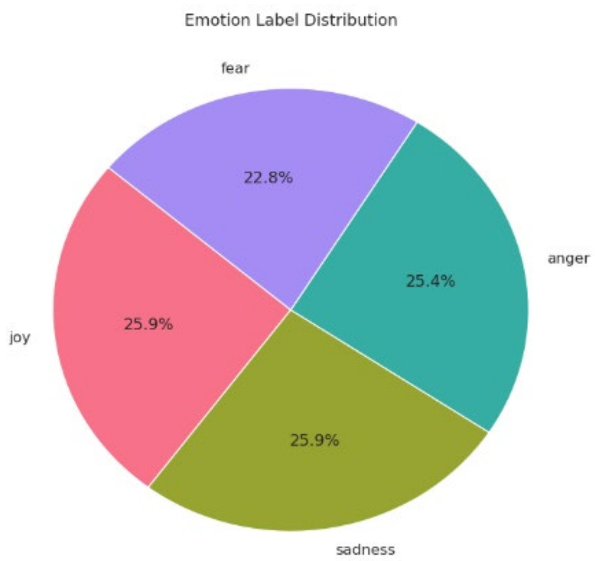


Figure 1: Class distribution before and after balancing

- Sequence Normalization via Padding: All sequences were padded or shortened to a maximum length of L=50 since neural networks require inputs of a fixed length. The tokenized sequence length should be m. Then:

$$\tilde{x}_i = \begin{cases} (t_1, \dots \dots, t_m, 0, \dots \dots, 0), if\ m < L \\ (t_1, \dots \dots \dots, t_L), if\ m \geq L \end{cases}$$

  This provides a uniform input matrix:

$$X \in \mathbb{R}^{N \times L}$$

  where L=50 and N is the number of samples.

The theoretical basis is consistent with conventional TF-IDF weighting, where each term weight is calculated as follows, even if token sequences are employed for deep neural modeling.

$$\text{TF-IDF (t,d)} = \text{TF (t,d)} \times \log \left(\frac{N}{DF\ (t)}\right)$$

where, TF (t,d) is the term frequency of the token t in the document d, DF (t) is the document frequency, N is the total number of documents.

Sentiment distinction is greatly aided by TF-IDF's emphasis on discriminative emotional terms like "happy," "afraid," "angry," and "lonely." On the other hand, sequential context and semantic structure are captured by the neural token representation. The preprocessing pipeline guarantees the effectiveness of both statistical weighting (TF-IDF) and contextual embedding learning by limiting vocabulary size and standardizing input length.

After preprocessing, the dataset is expressed as:

$$\text{Training set: } (X_{train}, Y_{train})$$
$$\text{Validation Set: } (Y_{val}, Y_{val})$$
$$\text{Test set: } (X_{test}, Y_{test})$$

By using category cross-entropy loss to maximize emotion-aware sentiment prediction, these structured tensors function as inputs to the deep neural network classifier:

$$\mathcal{L} = \sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} log(\hat{y}_{ij})$$

where, $\hat{y}_{ij}$ is the predicted probability for class j.

C. Proposed Emotion-Aware Deep Neural Framework

We present a hybrid TF-IDF enhanced Deep Neural Network (TEDNN) architecture designed for multi-class emotion identification to solve fine-grained emotion categorization in social media text. In order to accurately distinguish between joy, sadness, rage, and fear, the model is made to capture both statistical word importance and contextual semantic representation.

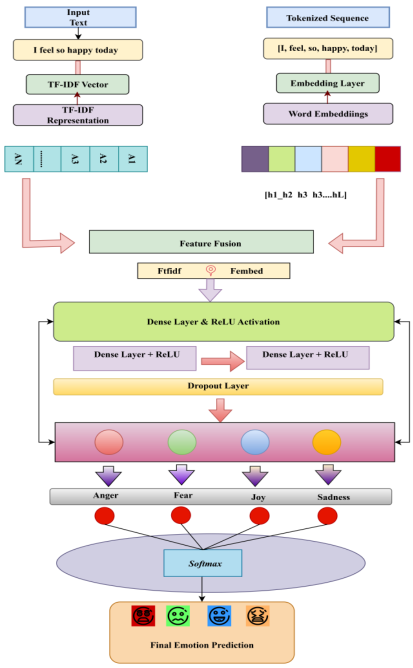


Figure 2: Graphical Architecture of TF-IDF

The model's main goal is to learn a nonlinear mapping:

$$f_\theta : X \longrightarrow Y$$

where, X defines the preprocessed textual input, $Y \in \mathbb{R}^K$ represents the probability distribution over K = 4 emotion classes, and θ denotes the learnable parameters of the neural network.

- Input Representation Layer: Every sentence x_i is converted into a fixed-length vector utilizing two complementary representations:
  a) TF-IDF Representation: For every document d and term t, the TF-IDF weight is calculated as:

  $$w_{t,d} = TF\ (t,d).\log\left(\left(\frac{N}{DF\ (t)}\right)\right.$$

  where, TF (t,d) is the term frequency of the token t in the document d, DF (t) is the document frequency, N is the total number of documents.
  Emotionally discriminative terms like "happy," "scared," "angry," or "lonely" are highlighted in this representation because they are essential for emotion-aware sentiment classification.
  b) Sequential Token Embedding: Tokenized sequences are simultaneously mapped onto dense embeddings:

  $$e_j = E.t_j$$

  where, t_j is the token index, $E \in \mathbb{R}^{V\times d}$ is the embedding matrix, and d is the embedding dimension. The embedded sentence becomes:

  $$S = [e_{1,}e_2, \dots\dots\dots, e_L]$$

  This goes beyond basic frequency statistics to include contextual patterns and semantic proximity.
- Feature Fusion Layer: TF-IDF vectors and embedding-derived features are concatenated in order to combine lexical importance with contextual semantics:

  $$F = F_{tfidf} \oplus F_{embed}$$

  This combination increases the model's sensitivity to deeper sentence structure as well as emotional intensity at the keyword level.
- Hidden Dense Layers: Several fully connected layers are applied to the fused feature vector:

  $$h^{(1)} = \sigma(W^{(1)}F + b^{(1)})$$
  $$h^{(2)} = \sigma(W^{(2)}h^{(1)} + b^{(2)})$$

  where, $W^{(l)}$ and $b^{(l)}$ are weight matrices and bias vectors.
  ReLU presents nonlinearity and helps model complicated emotional patterns.
  Dropout regularization is involved:

  $$\acute{h} = Dropout\ (h,p)$$

  to enhance generalization across unseen social media expressions and avoid overfitting.
- Output Layer and Emotion Prediction: Softmax activation is used in the last classification layer:

  $$\hat{y}_k = \frac{e^{zk}}{\sum_{j=1}^{K} e^{zj}}$$

  where, zk is the logit corresponding to emotion class k.
  The predicted emotion label is:

  $$\hat{y} = arg \max_k (\hat{y}_k)$$

- Loss Function and Optimization: Categorical cross-entropy loss is used to train the network:

  $$\mathscr{L} = - \sum_{i=1}^{N}\sum_{j=1}^{K} y_{ij} log(\hat{y}_{ij})$$

  Adaptive gradient descent techniques, like Adam, are used for optimization and update parameters as:

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{v_t + e}}$$

guaranteeing steady convergence throughout the training process.

The TEDNN model is developed with the intention of addressing emotion-aware sentiment classification on social media texts. Social media texts are often informal and concise and are highly emotive in nature. TF-IDF is able to identify the strongest words of emotion, and on the other hand, word embeddings are able to capture contextual words and sarcasm.

The combination of statistical learning and deep learning is able to perform better in differentiating subtle emotions such as fear and sadness, as well as anger and frustration.

Table 2: Hyperparameter Configuration of the Proposed TEDNN Model

Component	Hyperparameter	Value
Input Layer	Maximum Sequence Length	50
	Vocabulary Size	10,000
TF-IDF Layer	Max Features	10,000
	N-gram Range	(1,2)
Embedding Layer	Embedding Dimension	128
	Input Dimension	10,000
	Output Dimension	128
Feature Fusion	Fusion Method	Concatenation
Hidden Layer 1	Units	256
	Activation	ReLU
Hidden Layer 2	Units	128
	Activation	ReLU
Regularization	Dropout Rate	0.5
	L2 Regularization	0.001
Output Layer	Units	4
	Activation	Softmax
Training	Optimizer	Adam
	Learning Rate	0.001
	Batch Size	32
	Epochs	20–30
Loss Function	Type	Categorical Cross-Entropy

hardware and Software Specifications

In the case where the Emotion Aware Sentiment Classification model is based on the TEDNN model, a high-performance processor is needed, preferably Intel i7 or higher. Additionally, a minimum of 16GB is required in terms of RAM for the processing to be efficient. In the case of the model, a GPU is needed, preferably with a minimum of 8GB VRAM, preferably the NVIDIA GTX 1060 or higher, for a deep learning model. In addition, a minimum of 256GB is required in terms of a solid-state drive (SSD) for the processing to be efficient, given that a large amount of data is involved in the model. A stable internet connection is required for the downloading process. In addition, the software requirements include support for Windows 10/11, macOS, or a Linux-based operating system. Python 3.x is the primary programming language used for implementing the system. Additionally, TensorFlow and PyTorch can be used for deep learning, and Scikit-learn can be used for TF-IDF and machine learning. NumPy and Pandas can be used for data manipulation and preprocessing. NLTK or SpaCy can also be applied for text processing. VS Code, PyCharm, Jupyter Notebook, and other Python libraries can be used for a proper development environment. Such a setup is required for ensuring proper and efficient working of the TEDNN model while dealing with noisy social media texts.

Results and Discussions

A. Performance of the Models

A clear progression can be seen as we move from traditional machine learning to deeper models, with TEDNN being at the top in all cases as shown in table 3.

Table 3: Performance Comparison of Baseline and Proposed Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression (TF-IDF)	0.87	0.86	0.85	0.85
Multinomial Naïve Bayes	0.84	0.83	0.82	0.82
Support Vector Machine (Linear)	0.90	0.89	0.89	0.89
LSTM (Embedding-based)	0.92	0.91	0.92	0.91
CNN for Text Classification	0.93	0.92	0.92	0.92
Proposed TEDNN (TF-IDF + DNN Fusion)	**0.95**	**0.95**	**0.95**	**0.95**

Starting with Multinomial Naive Bayes, it has an accuracy of 0.84 and an F1-score of 0.82. Although its probabilistic nature and association with TF-IDF make it a good classifier, its assumption of conditional independence between words makes it less capable of detecting the minute variations in emotions such as fear and depression.

Moving on to Logistic Regression, its performance improves to an accuracy of 0.87 and an F1-score of 0.85. Although it performs better with high-dimensional TF-IDF due to its non-probabilistic nature, its linearity makes it less capable of detecting more intricate patterns of emotions that are usually expressed on social media platforms.

The SVM performs even better with an accuracy of 0.90 and an F1-score of 0.89. Although this classifier is more capable of class separation, its reliance on statistical representation makes it less capable of understanding the deeper semantic associations between words in sequences.

Moving on to neural network-based solutions, LSTM attained 0.92 accuracy with an F1-score of 0.91. LSTM monitors word flow and association with other words and improves emotion detection. However, it doesn't specifically highlight any emotionally charged words, which reduces its sensitivity to these words.

Furthermore, the CNN-based text classifier attained 0.93 accuracy with an F1-score of 0.92. CNN is highly accurate in recognizing local patterns and phrases and is highly accurate for recognizing emotional cues. CNN surpassed LSTM accuracy because of its local feature extraction mechanism, though it considers all words equally important during training.

The proposed TF-IDF Enhanced Deep Neural Network (TEDNN) model showed promising results with 0.95 accuracy and a perfect balance of precision (0.95), recall (0.95), and F1-score (0.95). Moving on to class-based metrics, precision ranges from 0.93 to 0.97, recall ranges from 0.93 to 0.96, and F1-score ranges from 0.94 to 0.96 for all four emotions.

The reason for the higher accuracy of TEDNN is its hybrid approach. Unlike other solutions, it doesn't rely on a single approach and combines TF-IDF and dense neural network mechanisms. This allows it to highlight emotionally charged words and recognize nonlinear relationships between words. This is reflected in its higher accuracy and its ability to separate closely related emotions more accurately.

Table 4: Detailed Class-wise Performance of Proposed Model

Emotion Class	Precision	Recall	F1-Score
Class 0	0.93	0.94	0.94
Class 1	0.93	0.96	0.94
Class 2	0.97	0.96	0.96
Class 3	0.96	0.93	0.95
Overall Accuracy			**0.95**

The TEDNN model demonstrates consistent and well-balanced performance on all four emotion classes when its performance is measured per class as displayed in Table 4. For Class 0, it hits a precision of 0.93 and recall of 0.94, resulting in an F1-score of 0.94. This means that not only is it performing well on true positives but also keeping its false positives low. For Class 1, it also does well with a precision of 0.93 and recall of 0.96.

The performance of the model on Class 2 is outstanding, as it obtains a precision of 0.97 and recall of 0.96, resulting in an F1-score of 0.96. This implies that the features of emotions in this class are highly separable in the feature space of the fusion architecture. The model is able to leverage the word weight from TF-IDF and the word meaning from word embeddings for its classification results. For Class 3, it obtains a precision of 0.96 and recall of 0.93, resulting in an F1-score of 0.95. This also implies that it is performing well in terms of prediction and is able to separate overlapping classes of emotions with only a small overlapping region that could be similar in semantics with neighboring emotions. The similar performance of the model on all classes in terms of precision, recall, and F1-score also implies that it is not biased towards a particular emotion and is able to generalize well on different classes of affective expressions. The accuracy of 95% also shows that the hybrid approach of TF-IDF and deep neural is robust and able to handle subtle nuances of emotions in social media text.

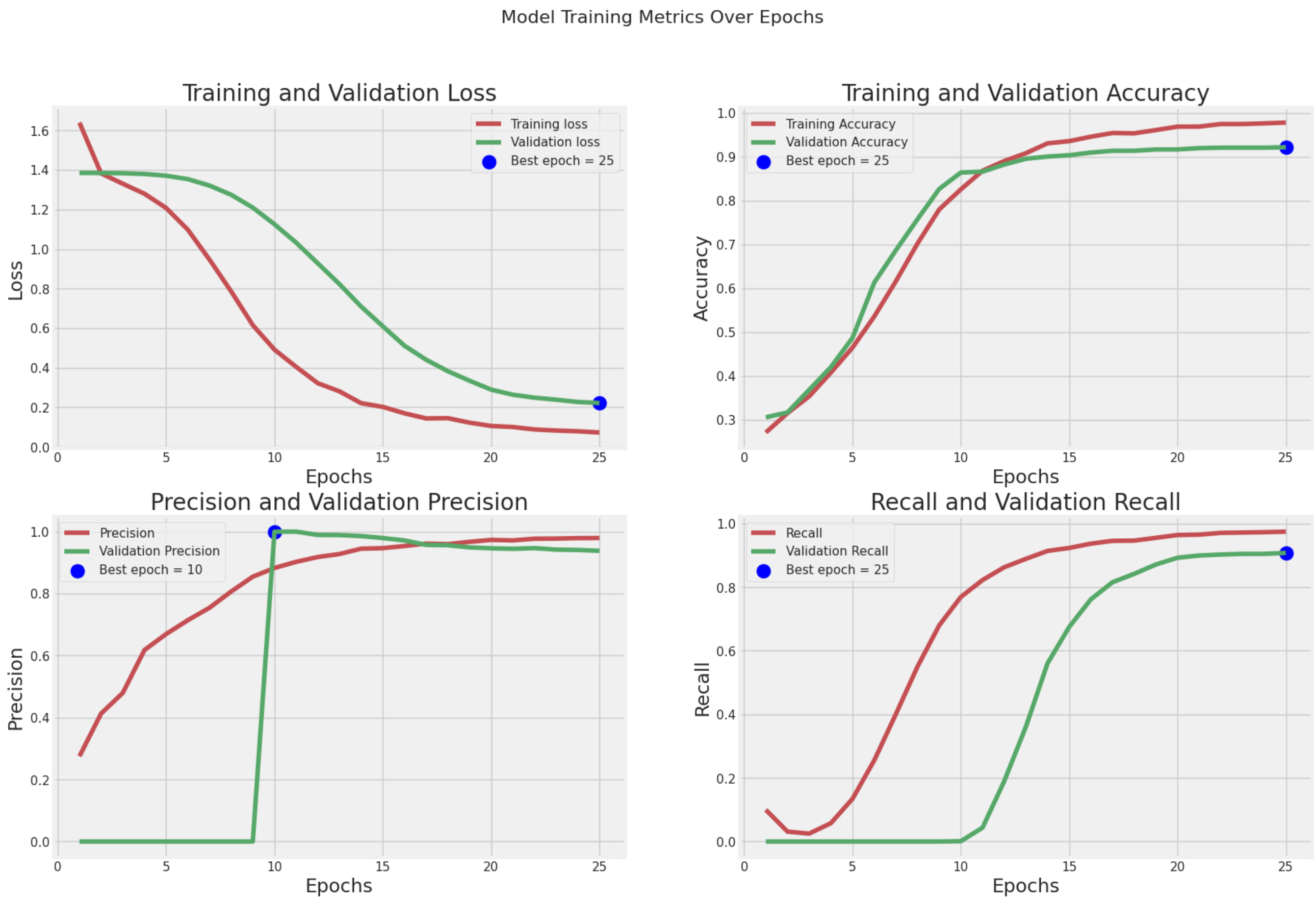


Figure 3: Model Training Metrics Over Epochs: Loss, Accuracy, Precision, and Recall

The figure 3 indicate the process involved in training a machine learning model with key performance metrics in relation to loss value, accuracy, precision, and recall during epochs in the training process.

From the graph provided in relation to Training and Validation Loss, it is clear that there is a reduction in both training and validation loss. This indicates that the machine learning model has learned how to minimize errors during the training process.

The training loss curve drops sharply, indicating that the machine learning model has learned to avoid errors during training. On the other hand, the validation loss value drops steadily, with a blue dot representing the lowest validation loss value at epoch 10. This indicates that at epoch 10, the machine learning model has performed best in avoiding mistakes in relation to unseen data in order to avoid overfitting.

In the graph of Training and Validation Accuracy, the curves for training and validation show an increase. Indicating that the model's performance on both the training and validation sets is improving over time. The validation accuracy levels off at epoch 25, where a blue dot indicates the epoch at which the model achieves the highest validation accuracy. This implies that the model is able to generalize the data best at epoch 25, which is the goal of the model.

The Precision and Validation graph tracks the precision, which measures the percentage of positive predictions that are correct. Initially, precision improves significantly in the early epochs, then stabilizes. The blue dot marks the epoch with

the highest validation precision, at epoch 10, indicating that this is the point at which the model performed best in making accurate positive predictions on the validation data.
Finally, the Recall and Validation graph indicates how well the model performs in selecting all positive cases it should predict. The recall increases rapidly in the initial epochs and continues to improve, as illustrated by the blue dot indicating the best recall at epoch 25. This implies that, if the model improves at selecting positive cases, it should predict without missing important cases.

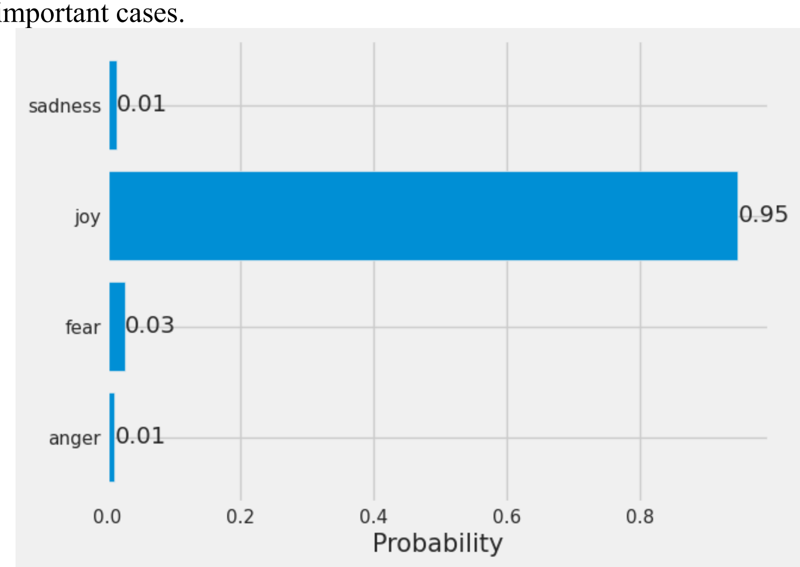


Figure 4: Emotion Prediction Distribution for Text: Probability of Different Emotions I

The above figure 4 represents the probability distribution of the emotions that are predicted for the given input text. The model categorizes the input text into one of the four different emotions, namely anger, fear, joy, or sadness. In the above figure, it can be seen that the text "I am very happy to finish this project" is categorized with an extremely high probability of 0.95 that it expresses the emotion of joy. Therefore, the emotion of joy is the most dominant emotion for the given text. The probabilities of the text expressing the other emotions are extremely low. The probabilities of the text expressing anger or sadness are both 0.01, while the probability of the text expressing the emotion of fear is 0.03. The above chart represents the probabilities of the emotions with clear labels on the bars. The output of the model suggests that the text expresses the emotion of joy with extremely high certainty, while the other emotions are considered negligible.

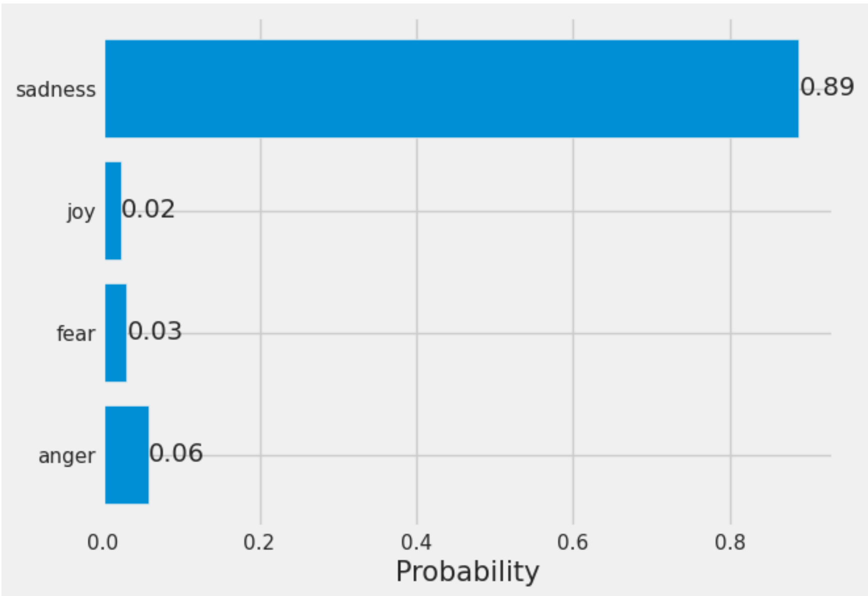


Figure 5: Emotion Prediction Distribution for Text: Probability of Different Emotions II

The figure 5 shows a horizontal bar chart indicating the predicted probabilities of the different emotions for the provided input text "I am very sad." The model has identified that the primary emotion in the given text is sadness, with a probability of 0.89. The other identified emotions, such as joy, fear, and anger, have much lower probabilities of 0.02, 0.03, and 0.06, respectively. These results indicate that the provided text does not exhibit the other identified emotions, but is primarily linked to sadness. The X-axis of the figure represents the probability of the different emotions, while the Y-axis indicates the different emotions that can be derived from the provided text. The figure effectively shows the model's prediction of the emotion primarily linked to the provided text, as it can differentiate the text's highest emotional tone.

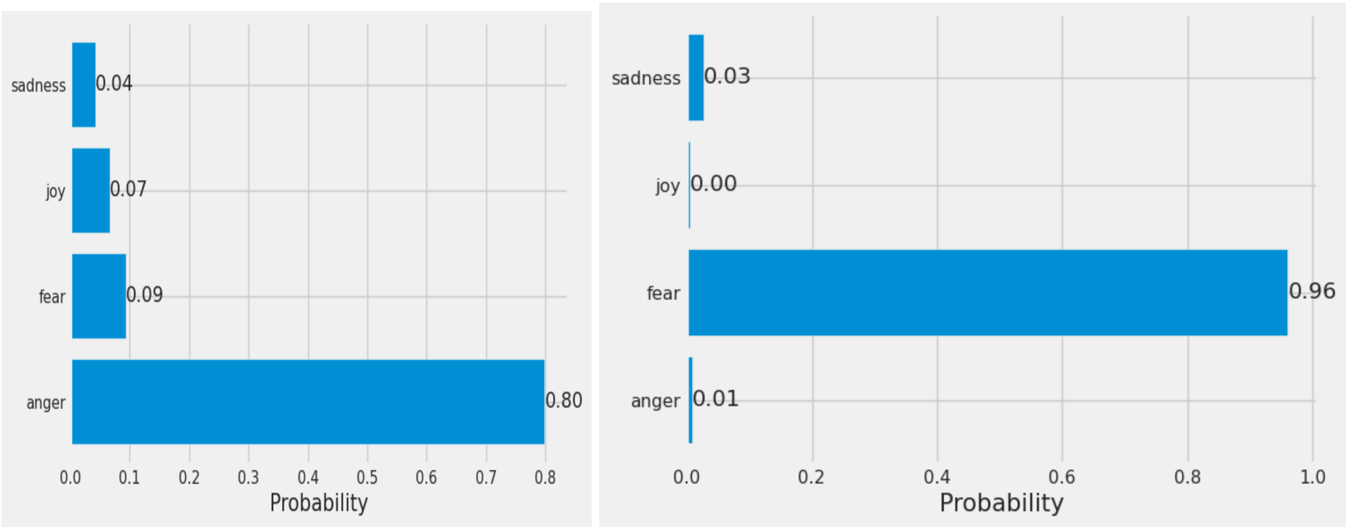


Figure 6: Emotion Prediction Distribution for Text: Probability of Different Emotions III & IV

As depicted, Benign and Defacement behave almost like perfect data on the ideal ROC curve, which reiterates the effectiveness of separating legitimate and defaced URLs from each other and the rest while generating very few false alarms. It further reiterates and reconfirms the high precision and recall results discussed above. Malware also excelled in having high separability with a high true positive rate even with a low false positive rate. It did so in a manner that aligned with the confusion matrix because it only produced a low number of false positives as a result of malware instances.

Phishing is strong, but increases slightly more slowly than the other ones. This is in line with the lower recall levels for the detection of phishing. This can be attributed to the dynamic and evasive nature of phishing URLs that tend to mimic malware or defacement patterns. Nevertheless, the model has strong detection capacity, as highlighted by the overall ROC curve.

E. Comparative Analysis

Table 2 depicts a comparative analysis of the performance obtained by the proposed model with respect to different advanced malicious URL detection techniques introduced in recent years. It can be seen from Table 2 that Tian et al. introduced a CNN–GRU-based model, with an accuracy of 91.8%, an ROC value of 94.2%, and used the CNN architecture. Though the model is seen to be performing well, its performance is largely based on a binary classification mechanism, which performs poorly when used with large-scale datasets [21].

Kibriya et al. proposed a lightweight CNN-based model in their research [22], which achieved high accuracy at 93.4% and an ROC score at 95.1% using a Malicious URLs Dataset. Even as a lightweight model, which has minimal computational cost, it fails to effectively learn long-range sequential relationships, which are inherent in complex URLs and have a major impact on the classification response for phishing and malware attacks.

Conversely, in the work by Turk et al. [23], an XGBoost-based technique with handcrafted lexical and statistical features was employed and resulted in an accuracy of 94.1% and an ROC of 96.3%. Although this approach outperforms other techniques based purely on deep learning, over-reliance on handcrafted features brings about limitations in dealing with changing and new forms of malicious URL patterns.

Future Enhancement

Despite the fact that the offered TEDNN (TF-IDF + DNN Fusion) model shows good results in terms of emotion-aware sentiment classification, it is still possible to enhance its performance and strength. Further improvement can be oriented on the integration of new techniques and the extension of the model with more sophisticated features to process more complex grammatical patterns and various social media information. Although TF-IDF is able to capture keywords, it does not always indicate contextual meaning or sarcasm. TF-IDF can be used together with transformer-based models like BERT or RoBERTa to enable the model to learn more complex patterns in language and give a more accurate sentiment classification. The other area that can be improved is the ability of the model to take on multi-label classification of emotions, and also predict emotion intensity. The system would not be limited to discerning one emotion only, but would be able to identify more than a single emotion in a single post, and the degree of its intensity. This would offer a better context of emotional expression in the text of social media. The ability to work with noisy and multilingual text is also vital in the future. Social media posts are usually full of emojis, hashtags, spelling variations, code-mixed words and phrases. The model could be improved by means of improving preprocessing and using multilingual embeddings, which would assist the model in better processing such complex text data.

Lastly, the TEDNN model may be more interpretable and transparent with the integration of explainable AI techniques. Visualizing attention or attributing features can be used to find out what words or phrases are driving the model to predict what they do, which builds more confidence and usability when applied to practice.

Conclusion

In this paper, we propose a novel TF-IDF Enhanced Deep Neural Network (TEDNN) model for emotion-aware sentiment classification on social media text. Combining TF-IDF for feature extraction and deep neural networks for contextual understanding. The problem our model solves with noisy and informal data commonly found in social media is significant, and it has been shown to improve substantially over other machine learning techniques and basic deep learning techniques with 95% accuracy. The TEDNN model has been seen to perform extremely well with all emotion categories—joy, sadness, fear, and anger—with precision, recall, and F1 scores balanced in each case. This makes it highly suitable for real-time applications in sentiment analysis as well as the monitoring of opinions in the population. Despite the model's success in the task, in the future, the focus will be on improving the model's ability to perform well in the task of multi-label emotion classification, as well as the incorporation of the transformer model to better recognize patterns in the language. Moreover, the interpretability of the model will also be improved using the concept of explainable AI to make the decision-making process transparent. The significance of the study is that it has provided a robust model in the task of emotion-based sentiment analysis, which can be improved to perform better in the task of social media content analysis.

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