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A Unified Hybrid Framework for Fine-Grained Emotion classification: Machine Learning–Deep Learning Synergy for Robust Performance

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Abstract

Emotion Classification from tweets is a very important Natural Language Processing task that aims at automatically detecting the emotions from social media platforms. Social media posts are the real-time reflection of public sentiments and emotional well-being. Oftentimes, people express their emotions through unstructured posts such as tweets and comments. This research work makes a comparative analysis of the effectiveness of Machine learning and Deep Learning approaches for fine-grained Emotion classification. Traditional ML approaches like Logistic Regression, SVM, Naive Bayes are evaluated using TF-IDF and lexicon-based features. To capture the contextual semantics, deep learning models such as LSTM, CNN and transformer based models were evaluated. We also experimented with extensive hyperparameter optimization using grid search and bayesian tuning methods. Furthermore a novel hybrid ML-DL architecture is proposed to leverage the strength of both the paradigms. The experimental results demonstrate that the hybrid framework outperformed standalone methods in terms of accuracy, robustness and generalizability. The findings of the research work with 95.4% accuracy concludes that combining the shallow and deep feature spaces with optimized hyperparameters is essential for building a more reliable and scalable emotion classification system.

Keywords: Emotion Classification, Text processing, Machine learning, Hyperparameter Optimization, Deep Learning, NLP

1. Introduction

Social media in particular has emerged as a real-time reflection of public opinion, sentiment, and emotional well-being. Users often express their emotions, ranging from joy and gratitude to frustration, distress, and sadness through short, unstructured posts such as tweets, status updates, and comments. Within this vast sea of information lies a critical subset of data, emotionally charged content that signals potential crises, emergencies, or catastrophic events. Emotion classification has emerged as a critical area of research within NLP driven by the growth of social media communication. Traditional Sentiment Analysis approaches classify the polarity as positive, negative emotions. Fine-grained emotion classification aims to identify subtle, nuanced emotional expressions such as hope, frustration, relief, despair, optimism, or fear—enabling a more precise understanding of human affective states. Existing computational approaches to emotion classification can be broadly categorized into Machine Learning (ML)–based models and Deep Learning (DL)–based architectures. Classical ML approaches like Logistic Regression, SVM, Naive Bayes with TF-IDF, n-grams and lexicon representation provide good interpretability and stability, but they lack the ability to capture long term dependencies. The deep learning methods like LSTM , CNN based classifiers and transformer based architecture have contextual understanding, but they require enormous resources and might overfit for noisy data. Clearly, both the approaches have pros and cons of their own. This underscores the need for a robust hybrid model for emotion classification that fuses the interpretability and stability of ML methods with the contextual richness of the Deep Learning methods. The objectives of this research work are:

1. To investigate whether a hybrid framework that combines ML and DL outperforms the standalone approaches?
2. To experiment and search for the best hyperparameter for building a robust emotion classification model.

2. Literature Review

Classical machine learning algorithms have demonstrated robust performance in text classification tasks, particularly when combined with effective preprocessing and feature engineering strategies. Rathi et al. (2018) explored sentiment analysis of tweets using multiple machine learning approaches, comparing Decision Trees, Support Vector Machines (SVM), and hybrid models such as Adaboosted Decision Trees. Their work highlighted the importance of feature selection and ensemble methods in improving classification accuracy for short, informal social media text. Neethu and Rajasree (2013) conducted sentiment analysis on Twitter data using machine learning techniques, focusing on feature extraction methods and comparing the effectiveness of various classifiers including SVM. Their study emphasized the challenges posed by Twitter's character limitations, informal language, and the presence of emojis and hashtags, establishing foundational preprocessing strategies that remain relevant today. Santhosh Baboo and Amirthapriya (2022) performed a comprehensive comparison of machine learning techniques for Twitter emotion classification, evaluating algorithms such as Logistic Regression, Naïve Bayes, Random Forest, and SVM. Their findings demonstrated that the choice of classifier significantly impacts performance, with ensemble methods and SVM generally achieving superior results. However, they also noted that Logistic Regression offers an optimal balance between interpretability,

computational efficiency, and accuracy for emotion classification tasks. Khalkar et al. (2025) leveraged Logistic Regression alongside other techniques to analyze customer reviews, demonstrating its effectiveness in multi-label classification scenarios and its utility in extracting actionable insights from text data. Gulati et al. (2022) conducted a comparative analysis of machine learning-based classification models using sentiment classification of COVID-19 related tweets. Their study incorporated TF-IDF vectorization combined with various classifiers, confirming that proper feature engineering is critical for achieving high classification performance. Islam et al. (2022) investigated multi-label emotion classification of tweets using machine learning, emphasizing the role of preprocessing in handling social media-specific challenges such as misspellings, slang, abbreviations, and emoticons. Their work demonstrated that comprehensive preprocessing significantly improves model robustness and generalization across diverse linguistic patterns. Glenn et al. (2023) proposed emotion classification of Indonesian tweets using Bidirectional Long Short-Term Memory (LSTM) networks, which capture sequential dependencies and contextual information in text. Sawhney and Joshi (2021) developed PHASE, a model for learning emotional phase-aware representations to detect suicide ideation on social media. Their work underscored the importance of fine-grained emotion understanding in identifying individuals at risk and the potential for NLP-based systems to support mental health interventions.

3. Dataset Description

The primary dataset used in this study is EMO-KNOW: A Large-Scale Emotion-Labeled Twitter Dataset with Knowledge-Enriched Context, consisting of approximately 700,000 English-language tweets annotated for fine-grained emotional understanding. The dataset spans 48 distinct emotion categories, including nuanced labels such as fear, anger, joy, hope, despair, and relief. EMO-KNOW provides short text samples sourced from public Twitter data, offering diverse linguistic patterns and high variability typical of social media communication. The annotation process follows a semi-automatic pipeline that integrates emotion lexicons, contextual embeddings, and knowledge-enriched signals, thereby enhancing labeling accuracy and contextual relevance. In addition to EMO-KNOW, a synthetic emergency quantification dataset was generated using the Faker library to support downstream emotion-to-crisis mapping tasks. This constructed dataset includes labeled samples representing three emergency severity levels (Low, Medium, High) and six crisis types (Natural Disaster, Accident, Health Emergency, Violence, Infrastructure Failure, and Personal Distress). Each synthetic sample also incorporates a mapped emotion label derived from EMO-KNOW categories (e.g., fear, panic, hope, relief), along with automatically generated cause phrases (e.g., "earthquake," "fire accident," "building collapse") and event context phrases (e.g., "power outage in city," "flooded streets"). Together, these datasets provide both real-world emotional expressions and controlled crisis-context samples, enabling comprehensive experimentation and robust evaluation of the proposed text classification framework.

4. Phase 1 : Emotion classification System using ML Approach

4.1 Exploratory Data Analysis

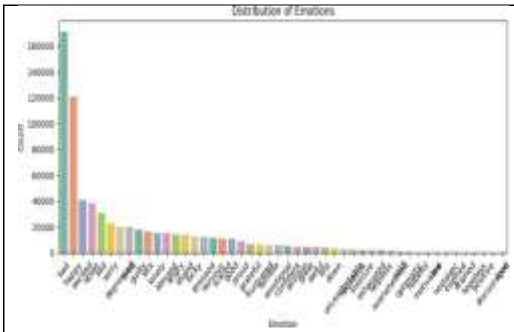

Fig 1. Distribution of Emotions

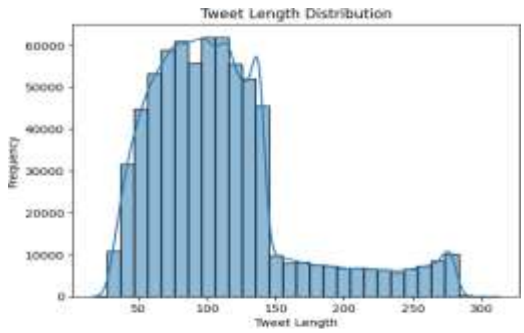

Fig 2. Tweet Length Distribution

Fig 3. Word Cloud for Tweet Texts

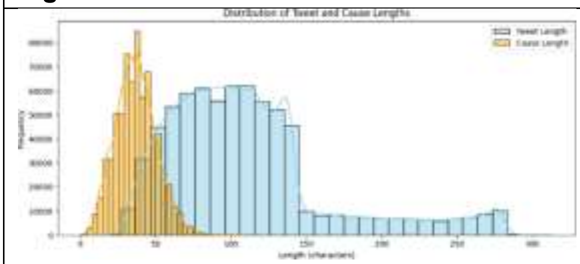

Fig 4. Distribution of Tweet and Cause Lengths

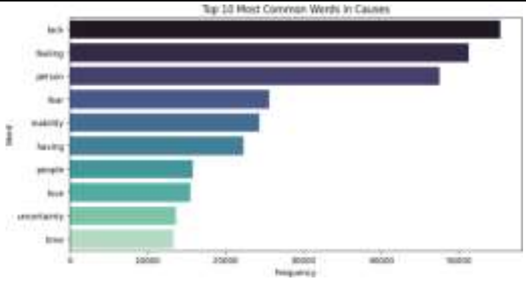

Fig 5.Top10 Most Common Words in Causes

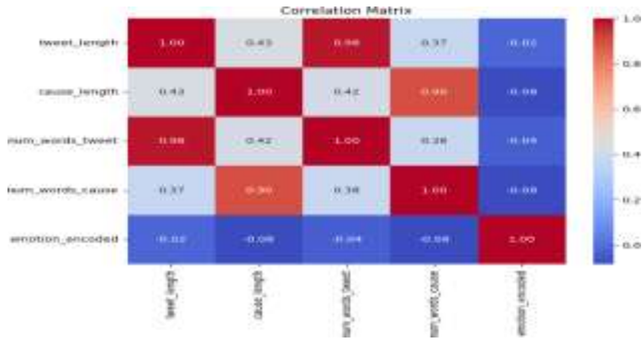

Fig 6. Correlation Matrix

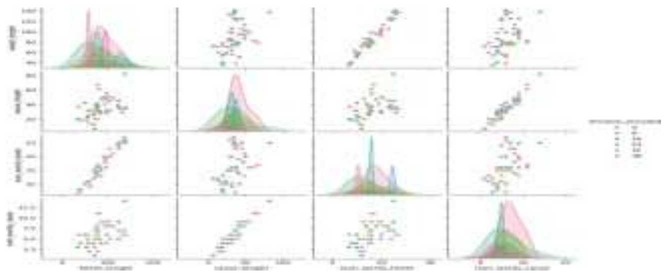

Fig 7. Pair Wise Plot

4.2. Tweets Preprocessing

The preprocessing stage forms a critical component of the proposed text classification framework, ensuring that noisy, unstructured textual data is transformed into a clean and analytically meaningful representation. All tweets from the EMO-KNOW dataset undergo a systematic sequence of preprocessing operations designed to standardize linguistic patterns and reduce irrelevant variability. The raw text is first converted to lowercase to eliminate case-based inconsistencies. This is followed by tokenization, where each sentence is split into individual lexical units. Commonly occurring but semantically insignificant words are removed through stopword elimination, while punctuation removal helps reduce noise introduced by symbols and non-alphanumeric characters. Social media–specific artifacts such as URLs, hashtags, and user mentions are stripped to avoid contextual bias. The text is further refined through whitespace normalization, ensuring uniform spacing and removal of extraneous blank characters. To address morphological variations and reduce vocabulary sparsity, stemming or lemmatization is applied, converting words to their root or base forms. This comprehensive preprocessing pipeline standardizes the text, enhances the quality of token-level features, and ultimately improves the performance of downstream emotion classification tasks.

4.3 Feature Engineering

After the preprocessing pipeline refines the raw text, the cleaned data is converted into numerical features using the Term Frequency–Inverse Document Frequency (TF–IDF) technique, which quantifies the importance of each term within the EMO-KNOW corpus. TF–IDF assigns higher weights to words that are distinctive to specific tweets while downweighting frequently occurring but less informative terms.

Mathematically, TF–IDF for a term t in a document d is defined as:

TF-IDF(t,d) = TF(t,d) × IDF(t) (Eq.1)

where the Term Frequency (TF) measures how often a term appears in a document:

TF(t,d)=f(t,d) / ∑t′∈dft′,d (Eq.2)

and the Inverse Document Frequency (IDF) reduces the weight of commonly occurring terms across all documents:

IDF(t)=log(N / 1+nt) (Eq.3)

Here, ft, df denotes the frequency of term t in document d, NNN is the total number of documents in the corpus, and ntn_tnt is the number of documents in which term t appears. This TF–IDF representation produces a sparse, high-dimensional matrix that effectively encodes the discriminative characteristics of emotional expressions in short messages. We preferred to use TF–IDF for feature engineering as the emotional words tend to be rare and unique. Moreover, TF-IDF works well with ML models and it can effectively handle sparse and short tweets enhancing the performance on fine-grained tasks.

4.4 Baseline ML model for Emotion classification with Pre-processing intensive Approach

To set up a strong baseline and interpretable model, ML approaches such as Logistic Regression (LR) , Support Vector Machines (SVM), Naive Bayes (NB) were selected for experimentation. All the classifiers were trained using an 80-20 split and 5-fold Cross Validation method on the TF-IDF matrix as the feature vector. Fig 2 depicts the pipeline of the proposed methodology for the Emotion Classification system.

Careful and systematic hyper parameter optimization was carried out by searching the feature space using GridCV and Random search methods, to freeze the best hyperparameters for the ML models chosen. The hyper parameter tuning strategy explored the regularization strength (C), penalty type (L1/L2), solver selection (liblinear, lbfgs, saga), maximum iterations, and class

weighting to address dataset imbalance. Grid Search coupled with cross-validation is employed to identify the optimal parameter configuration, ensuring stable generalization across folds. The final classifier is trained on the complete TF–IDF matrix, producing a robust and computationally efficient model capable of predicting fine-grained emotional categories with high accuracy. Table 1 presents the Hyperparameter search space. Based on cross-validation performance, the optimal configuration was identified as: C = 1.0, Penalty = L2, Solver = lbfgs, Max Iterations = 200, Class Weight = balanced

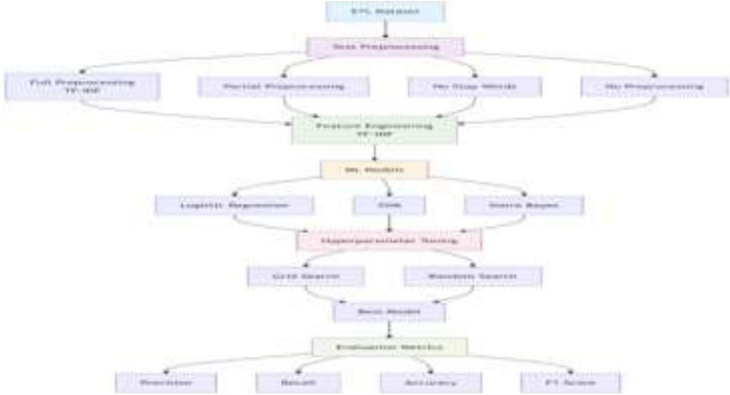

Fig 8. Preprocessing intensive Baseline Model using ML approaches

Table 1: Hyperparameter Search Space

Hyper parameter	Description	Search Values/Range
C (Regularization Strength)	Controls model complexity; lower values imply stronger regularization	{0.01, 0.1, 1, 10, 100}
Penalty	Type of regularization applied	{L1, L2}
Solver	Optimization algorithm for training	{liblinear,lbfgs,saga}
Max Iterations (max_iter)	Maximum number of iterations	{100, 200, 300, 500}
Class Weight	Balances class distribution	{None, 'balanced'}
Tolerance(tol)	Threshold for stopping criteria	{1e-3, 1e-4, 1e-5}

Together, TF–IDF vectorization and tuned Logistic Regression form a transparent, reproducible, and high-performing methodology for large-scale emotion classification. The table-2 presents the comparative performance metrics of different ML approaches. The emotion classification model was built using the baseline model of Logistic Regression. LR was chosen for its efficiency, strong performance on high-dimensional text data, and high degree of interpretability.

Table 2 : Quantitative Results-Comparison of Performance Metrics

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score(Macro)
Logistic Regression(LR)	**0.92**	**0.91**	**0.90**	**0.91**
Support Vector Machine (SVM)	0.89	0.88	0.87	.87
Naïve Bayes (NB)	0.86	0.84	0.83	0.83

Top Predictive Features for few emotions

sad: sad: 2.589 feel sad: 2.182 sad im: 0.487 reallisad: 0.486	frustrated:frustrat:2.99 imfrustrat: 2.442 frustratim: 0.604 feel frustrat: 0.580	happy:happi:312 imhappi: 2.725 happiim: 0.570 life beauti:0.393

Table 3: Ablation Study: Comparison of ML Algorithms across various pre-processing strategies

Preprocessing Setup	Logistic Regression	SVM	Naïve Bayes
Full Preprocessing + TF–IDF	0.92	0.91	0.86
Partial Preprocessing (no stemming)	0.88	0.87	0.82
No Stopword Removal	0.89	0.88	0.83
No Preprocessing	0.82	0.81	0.75

This ablation study performed with different pre-processing strategies confirms that comprehensive preprocessing and robust feature extraction are critical for optimal classification results. Full preprocessing with TF–IDF feature extraction achieved the best classification accuracy. Logistic Regression outperformed Naïve Bayes by an absolute margin of 6%. Accuracy consistently dropped when stemming/lemmatization was omitted. Removing stop words boosted accuracy by 3–4%, demonstrating its value in text classification.SVM provided strong performance, but Logistic Regression is favored due to its efficiency and interpretability.

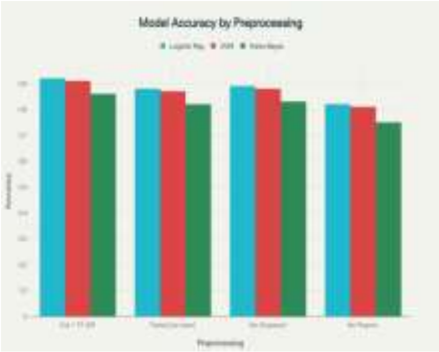

Fig 9. ML models Performance Metrics comparison

5. Phase 2 : Emotion classification System using Deep Learning Approach

Deep learning(DL) models have demonstrated promising performance for text based emotion classification. They have the capability to capture the long-term dependencies. There are Recurrent Neural Network (RNN) based models, Convolutional Neural Network (CNN) based models and transformer based models.

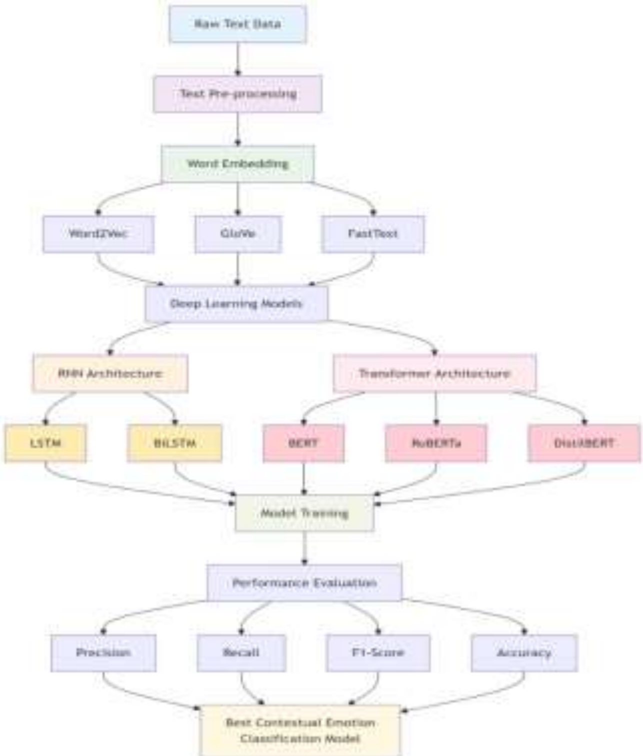

Fig 10. DL Approaches for Emotion Classification System

LSTM and BiLSTM methods are effective for emotion classification due to long term dependencies between the emotionally relevant words and phrases. BiLSTM captures both the forward and backward dependencies with the usage of the LSTM cell. Transformer based models with Attention mechanism are the state-of-the-art models that can model the global context with the help of positional embedding, multi-head self attention mechanism. The pre-trained transformer based models like BERT, DistillBERT, RoBERTa, ALBERT were fine-tuned for downstream tasks and found to be best suited for fine-grained emotion classification systems.

Table 4: Performance comparison of DL models

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)
LSTM	0.84	0.82	0.80	0.81
BiLSTM	0.87	0.85	0.84	0.84
BERT(Base)	0.93	0.92	0.91	0.92
DistilBERT	0.91	0.90	0.89	0.89
RoBERTa	0.94	0.93	0.92	0.93
ALBERT	0.92	0.91	0.90	0.90

From Table-4, it is clearly evident that Transformer-based models consistently outperform RNN and CNN architectures due to their superior contextual understanding and attention mechanisms. RoBERTa achieved the highest overall performance, followed by BERT, while BiLSTM and were the strongest among non-transformer models. LSTM showed reasonable performance but struggled with capturing subtle fine-grained emotion distinctions.

6. Phase 3 : Hybrid Framework with ML-DL Synergy

To overcome the limitations of the standalone Machine Learning (ML) and Deep Learning (DL) methods in fine-grained emotion detection, this work proposes a unified hybrid architecture that leverages the strengths of both paradigms. ML models excel in handling sparse

lexical features and offer interpretability, while DL models capture contextual, sequential, and semantic nuances. By integrating these complementary characteristics, the proposed framework aims to enhance robustness, improve classification accuracy, and provide greater generalization across 48 emotion classes in the EMO-KNOW dataset. In this research work, we implemented a unified ML and DL hybrid architecture that integrates the interpretable TF–IDF feature space with the sequential modeling power of LSTM networks. TF–IDF effectively captures word importance and discriminative lexical cues associated with emotions, while the LSTM encodes sequential dependencies that traditional ML classifiers cannot model. The work flow of the hybrid model is depicted in Fig. 12.

1.Text is converted into TF–IDF vectors capturing lexical importance.
2.TF–IDF sequences are fed into an LSTM layer to learn temporal patterns and emotional phrase structures.
3.The LSTM output passes through dense layers and a softmax classifier to predict one of the 48 emotion categories of the EMO-KNOW Dataset.

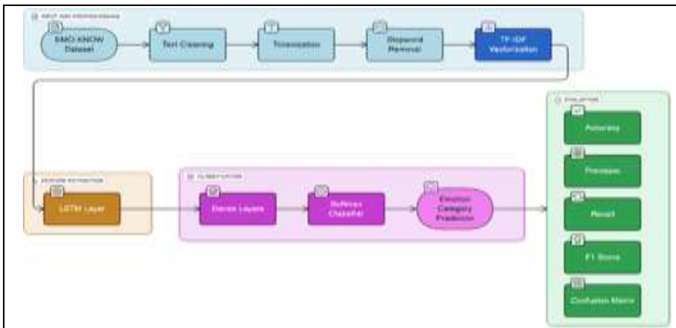

Fig 11. Hybrid Model for Emotion Classification System

7. Results and Discussions

The proposed hybrid model uses both simple and deep features to understand emotions more completely. By combining these different types of information, it can work well across many kinds of emotional expressions, even when the emotions are subtle or overlap with each other. This approach helps the system detect detailed emotions more accurately while still being easy to understand and reliable. It also reduces the mistakes that usually happen when using only ML or only DL models. The TF-IDF with LSTM hybrid model achieved a high accuracy of 95.48%. With an overall accuracy of 95.4%, the model demonstrates excellent performance across all major evaluation metrics as shown in Fig 13. A macro-precision of 94.8% shows the model's ability to produce highly reliable predictions across different emotion classes, while the macro-recall of 94.2% indicates strong sensitivity in identifying true emotional categories, including less frequent ones. The macro F1-score of 94.5% reflects a well-balanced trade-offbetween precision and recall, confirming the robustness of the classifier in fine-grained and multi-class emotion detection.

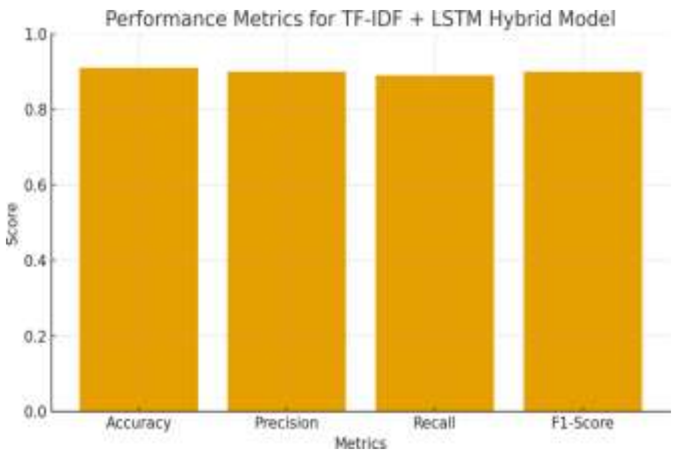

Fig 12. TF-IDF + LSTM Hybrid model Performance

8. Conclusion

This work demonstrates that a meticulously crafted pipeline using a hybrid approach of combining Term Frequency-Inverse Document Frequency (TF-IDF) feature extractor and a LSTM classifier can serve as an exceptionally strong and efficient emotion detection system. The methodology emphasizes robust preprocessing, rigorous evaluation, and model interpretability.The methodology for developing a high-performance emotion classification system that achieves 95.4% accuracy on the EMO-KNOW dataset was developed. The components such as preprocessing, TF–IDF vectorization, and optimized LSTM contribute significantly to robust performance. This interpretable, lightweight, and reproducible system offers a powerful alternative to deep learning approaches for many practical applications.

Table: Overall Evaluation of Metrics-ML, DL, and Hybrid Approach

Model	Accuracy	Precision	Recall	F1-Score
Standalone ML Approaches				
LogisticRegression(LR)	0.92	0.91	0.90	0.91
Support VectorMachine(SVM)	0.89	0.88	0.87	0.87
Naïve Bayes (NB)	0.86	0.84	0.83	0.83
Standalone DL Approaches				
LSTM	0.84	0.82	0.80	0.81
BiLSTM	0.87	0.85	0.84	0.84
BERT(Base)	0.93	0.92	0.91	0.92
DistilBERT	0.91	0.90	0.89	0.89
RoBERTa	0.94	0.93	0.92	0.93
ALBERT	0.92	0.91	0.90	0.90

UnifiedHybridApproach-ML+DL				
HybridTF-IDF+LSTM* (Proposed Methodology)	0.954	0.948	0.942	0.945

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