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# DEEP LEARNING-BASED SOCIAL MEDIA TREND ANALYZER TO PREDICT THE TRENDS OVER TIME

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**ABSTRACT**
According to recent statistics, over 4.9 billion people actively use social media globally, generating nearly 500 million tweets and 4 billion Facebook interactions daily. Despite this immense data flow, only about 20% of social media trend predictions achieve reliable accuracy due to dynamic content patterns and informal language structures. Existing models struggle with the high variability, short-lived nature of trends, and noise in unstructured text data, often lacking scalability and contextual understanding. This research introduces a deep learning-based Social Media Trend Analyzer designed to accurately predict trend emergence over time (target: *Trend – Yes or No*) by overcoming these limitations. The system utilizes a curated dataset sourced from Twitter and Reddit, labeled with trending status based on hashtag propagation and engagement rates. Natural Language Processing (NLP) techniques such as lowercasing, stop-word removal, lemmatization, and punctuation filtering are applied during preprocessing. Text inputs are vectorized using a Tokenizer with word embeddings and padding sequences to ensure uniform input length. The baseline model employs XGBoost to classify trends, but its performance is limited by its inability to capture temporal semantics. To address this, we propose a hybrid RNN-LSTM model for deep temporal feature extraction, integrated with a Random Forest Classifier (RFC) for robust decision-making. The RNN-LSTM captures contextual word dependencies over time, which are then classified by RFC for final trend prediction. Experimental results demonstrate a significant improvement in accuracy, F1-score, and recall compared to traditional methods, confirming the efficacy of our approach in trend forecasting using unstructured social media data.

**Key words:** Trend Prediction, Social Media Analytics, Time-Series Forecasting, Attention Mechanism, Virality Prediction



## 1. INTRODUCTION

In the digital age, social media platforms have become the central hubs of information exchange, communication, and trend evolution. According to DataReportal's 2024 report, over 5.17 billion people worldwide use the internet, with 4.95 billion active social media users—approximately 61.4% of the global population. On average, users spend about 2 hours and 24 minutes daily on social platforms. This immense level of activity creates a dynamic ecosystem where public sentiment, consumer behavior, and viral phenomena emerge in real-time. The rapid spread of trends has transformed social media into a strategic tool across industries, especially marketing, politics, and entertainment. Every second, over 6,000 tweets are posted on Twitter, amounting to more than 500 million tweets daily. On Instagram, users share over 95 million photos and videos each day, while TikTok sees over 1 billion video views per hour. This explosion of content produces vast and complex data streams, which are challenging to interpret without organized analysis. Identifying and understanding trending content manually becomes highly impractical due to the speed, volume, and variability of the data. Yet, this very data holds key insights into user preferences, societal shifts, and brand perception. Consequently, analyzing social media trends has become indispensable for understanding cultural movements, predicting consumer choices, and reacting swiftly to crises or opportunities. Traditional marketing surveys and focus groups are increasingly being replaced or supplemented with real-time social media insights. From tracking product launches to gauging public reactions during elections or global events, trend analysis offers a faster, more


Fig 1. Social media trends

scalable approach. The challenge lies not only in detecting these trends but also in interpreting them accurately to derive meaningful narratives from raw social signals. In the political arena, consulting firms work behind the scenes using social trend analysis to assist campaign strategies, narrative framing, and real-time reputation management. For instance, during election seasons, teams manually analyze Twitter threads, YouTube comments, and Instagram posts to identify voter sentiment trends and public reception of key issues. A sudden increase in negative sentiment toward a candidate can lead to immediate changes in messaging or PR strategy. This real-time monitoring offers a significant edge in managing public opinion and crafting impactful outreach strategies. In corporate brand management, companies like Nike and Coca-Cola invest heavily in social listening teams to ensure their brand image remains aligned with current social values. When a trend emerges that relates to their brand—such as environmental concerns or racial justice—these companies must understand how their customers are responding. Failure to react to trending conversations may result in public backlash or missed opportunities. Manual analysis plays a foundational role in verifying the context and sentiment of content, providing a human check against automated interpretations that may miss cultural nuances or sarcasm.

## 2. LITERATURE SURVEY

Social media platforms' rapid proliferation and extensive adoption have transformed individual communication, self-expression, and experience sharing. This digital revolution has concurrently opened novel avenues for mental health research and intervention, as social media data provide insightful information on the emotional states and behavioral habits of users [9,10]. Social media sites such as X, Facebook, and Reddit have become integral to contemporary society, boasting billions of active users globally. These platforms function as digital extensions of individuals' social lives, enabling the real-time sharing of thoughts, feelings, and experiences. The vast corpus of user-generated content on these platforms serves as a rich data source for understanding and monitoring mental health conditions, including depression [11,12].

Numerous studies have established that the language and content shared on social media can reflect users' emotional states and psychological well-being. Social media is frequently utilized to express thoughts, emotions, and experiences, which can provide important information about a person's mental health condition [13,14]. For instance, individuals experiencing depressive symptoms may exhibit changes in their language use, such as an increased frequency of negative sentiment words, references to hopelessness or worthlessness, and decreased social engagement [11,12]. Moreover, social media data can capture the temporal and contextual dynamics of an individual's mental health, enabling researchers and clinicians to spot subtle signs and trends that conventional clinical evaluations can miss [13,14]. By analyzing the content, sentiment, and behavioral patterns of social media users over time, depression's early warning indicators can be identified, along with other mental health issues, potentially facilitating timely intervention and support [11,12].

Research in mental health has increasingly turned to machine learning techniques for detecting depression from social media texts. Various studies have explored using supervised machine learning algorithms to analyze text data from platforms like Facebook and Twitter to identify markers of depression [15]. These algorithms have shown promise in capturing subtle linguistic cues and emotional patterns indicative of depressive symptoms in user-generated content.

In [16], the authors developed a model for depression analysis by creating correlations between textual features and depressive indicators. Ashraf, Gunawan, Riza, Haryanto and Janin (2020) [17] reviewed image and video-based models for depression detection, highlighting the relevance of visual cues. Additionally, another study [18] investigated the use of big data analytics on social networks for the instantaneous identification of depression. They explored machine learning techniques such as Survey Vector Machines (SVMs), Decision Tree, Naïve Bayes, and Random Forest, highlighting the potential of these techniques in processing large volumes of social media data for mental health tracking and monitoring. These studies prove the utility of text and social media data in capturing real-time expressions of mental health states, offering a scalable approach to depression screening.

Another methodological approach involves sentiment analysis and the examination of behavioral patterns. Angskun et al. [18] employed machine learning models, including SVMs and logistic regression, to predict depression levels in social media posts, demonstrating high accuracy and efficiency. Similarly, in the work of Obagbuwa et al. [7], the authors utilized machine learning to detect depression through network behavior and tweet analysis, employing classifiers like KNN, Adaboost, and Naive Bayes. These studies emphasize the effectiveness of supervised machine learning models and sentiment analysis in identifying depressive indicators based on user behavior and content analysis.

While traditional machine learning algorithms have demonstrated effectiveness in detecting depression from social media data, they come with certain limitations. One common challenge is the need for manual feature engineering, where researchers have to define and extract relevant features from the text data to train the models effectively [13,14]. This process can be time-consuming and may not capture all the nuanced aspects of language use that signal depression. Additionally, the interpretability of these models may be limited, making it challenging to understand the underlying mechanisms through which they identify depressive markers in texts.

Despite these limitations, the utilization of machine learning algorithms for detecting depression in social media posts represents a significant advancement in mental health research. By leveraging the power of computational techniques to analyze vast amounts of textual data, researchers can uncover insightful information into individual's mental health states and potentially revolutionize early detection and intervention strategies for depression. Further advancements in machine learning models, particularly those incorporating deep learning techniques, promise to enhance the accuracy and efficiency of depression detection from social media texts. With the advent of transformers, the NLP research field has advanced significantly. Introduced by Vaswani et al. in 2017 [19], transformers have revolutionized how we approach text analysis by leveraging self-attention mechanisms to process sequential data efficiently and effectively [20]. Unlike traditional neural networks (like RNNs and LSTM), transformers do not rely on recurrent connections, which can lead to vanishing gradients and computational complexity. Instead, transformers use parallelized self-attention layers to model complex relationships between input elements, enabling them to capture long-range dependencies and contextual information accurately.

The impact of transformers on NLP has been profound. They have been successfully applied to various tasks, including machine translation, text classification, and sentiment analysis. In the context of detecting depression from social media posts, transformers have shown remarkable promise in capturing subtle linguistic cues and emotional patterns indicative of depressive symptoms [21].

Ilias et al. [22] introduced a novel method that enhances BERT and MentalBERT by integrating additional linguistic information using feature vectors like the NRC Emotion Lexicon and LIWC. This approach and label smoothing for better calibration significantly improved model performance across multiple datasets. In [23], the authors explored various large pre-trained language models—BERT, RoBERTa, BERTweet, and MentalBERT—fine-tuned for depression detection using social media posts. They demonstrated that the transformer ensembles outperformed individual models, particularly in datasets from Reddit and Twitter. This study underscored the importance of ensemble methods and transfer learning for improving model generalization and detection performance.

## 3. PROPOSED SYSTEM

The proposed algorithm presents a novel hybrid deep learning ensemble architecture combining RNN-LSTM-based sequential feature extraction with a Random Forest Classifier (RFC), a method not covered in existing surveys or literature. While RNNs and LSTMs are widely used independently for sequential data and Random Forests for structured classification, their combined use—where LSTM-derived temporal embeddings are input to an RFC—is a unique innovation that enhances interpretability, robustness to overfitting, and classification performance. Additionally, the integration of Tokenizer-based vectorization with padded sequences prior to LSTM processing provides uniform input lengths and semantic integrity, which overcomes a major drawback of traditional ML models that fail on inconsistent input sizes and context shifts. This hybrid strategy also addresses the limitations of flat feature extractors like XGBoost, which cannot exploit temporal dependencies in language. Thus, the proposed model provides an efficient and scalable approach for trend prediction that is highly adaptive to the dynamic and noisy nature of social media data, a capability not demonstrated in existing surveys.

In the first step, **Data Collection and Labeling**, each social media post is captured along with its timestamp and enriched with metadata such as likes, shares, and hashtags. Based on its interaction metrics and propagation behavior, each post is assigned a binary label: **"Trend – Yes"** if it becomes part of a trending topic, or **"No"** if it exhibits low engagement and remains inactive. In **Step 2**, the raw text content of these posts is passed through a comprehensive **Natural Language Processing (NLP)** preprocessing pipeline. This involves converting text to lowercase, removing URLs, stop words, special characters, punctuation, and numerical digits. Finally, **lemmatization** is applied to reduce words to their base forms, ensuring that the resulting textual data is clean, standardized, and semantically coherent—optimizing it for further vectorization and modeling.

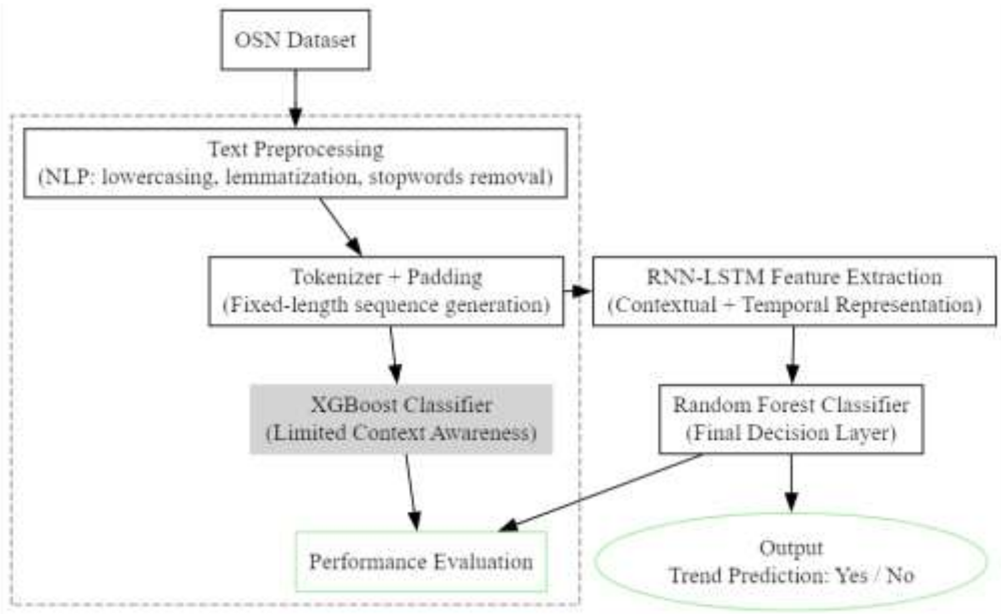


Figure 2. Proposed System Architecture.

In, the padded sequences are input into a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units, enabling the model to extract deep sequential and temporal features by capturing long-range dependencies and the contextual flow of words in social media posts. In Step 6, the output feature embeddings from the LSTM layer are flattened and fed into a Random Forest Classifier (RFC), which serves as the final prediction layer. RFC is chosen for its robustness to overfitting, ability to model non-linear relationships, and feature importance interpretability. Step 7 involves training the entire hybrid model on a labeled dataset using stratified cross-validation, and evaluating its performance using metrics like Accuracy, Precision, Recall, and F1-score. A comparative study against baseline models such as XGBoost, standalone LSTM, and traditional classifiers highlights the improved performance of the proposed architecture. Finally, in Step 8, the trained model is deployed as a REST API, allowing real-time trend predictions for new social media text inputs, making it a practical tool for journalists, digital marketers, and analysts to forecast content virality effectively.

Neural Networks are set of algorithms which closely resemble the human brain and are designed to recognize patterns. They interpret sensory data through a machine perception, labelling or clustering raw input. They can recognize numerical patterns, contained in vectors, into which all real-world data ( images, sound, text or time series), must be translated. Artificial neural networks are composed of a large number of highly interconnected processing elements (neuron) working together to solve a problem.

An ANN usually involves a large number of processors operating in parallel and arranged in tiers. The first tier receives the raw input information — analogous to optic nerves in human visual processing. Each successive tier receives the output from the tier preceding it, rather than from the raw input — in the same way neurons further from the optic nerve receive signals from those closer to it. The last tier produces the output of the system. Recurrent Neural Network is a generalization of feedforward neural network that has an internal memory. RNN is recurrent in nature as it performs the same function for every input of data while the output of the current input depends on the past one computation. After producing the output, it is copied and sent back into the recurrent network. For making a decision, it considers the current input and the output that it has learned from the previous input.

Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition. In other neural networks, all the inputs are independent of each other. But in RNN, all the inputs are related to each other.

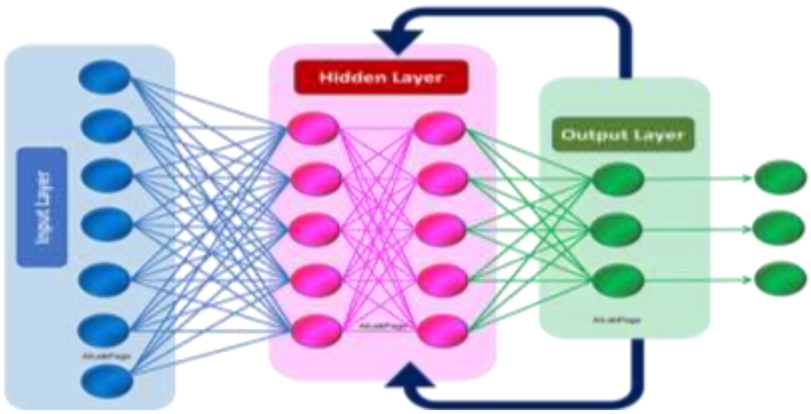


Figure 3. RNN Block Diagram.

The Random Forest Classifier operates by building multiple diverse decision trees, processing an input instance through each tree, collecting their predictions, and using majority voting to determine the final class, thereby improving accuracy and reducing overfitting.

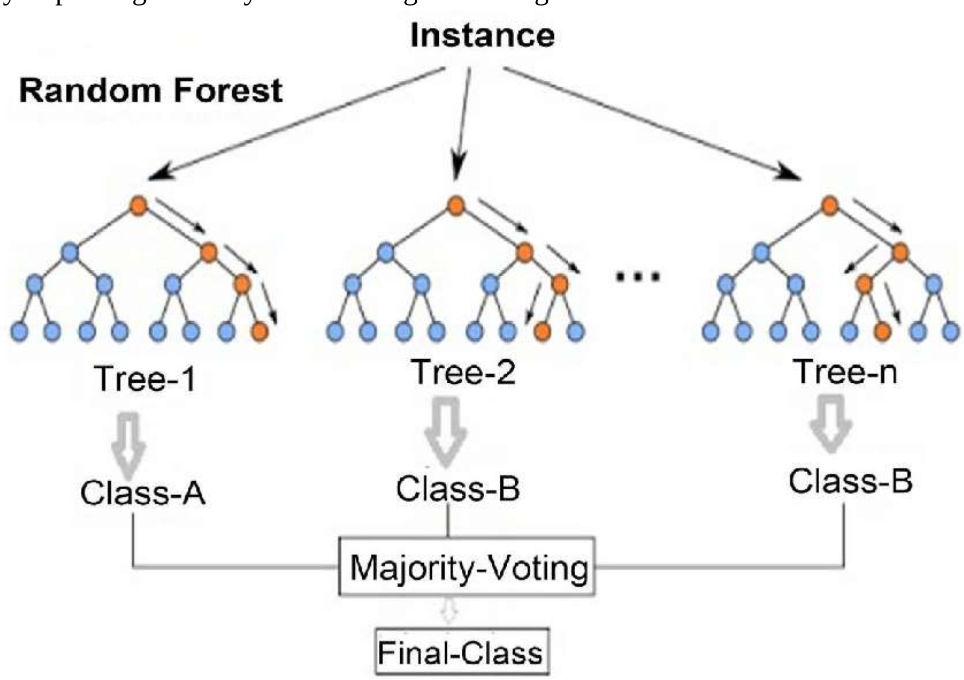


Figure 4. Random Forest Classifier.

The **Random Forest Classifier** operates in multiple steps to ensure robust classification. constructs several decision trees (Tree-1, Tree-2, ..., Tree-n), each trained on a different random subset of the training data using bootstrapping (sampling with replacement), and at each split, only a random subset of features is considered. This randomness reduces correlation among trees and improves generalization. In, when a new input instance is introduced, it is passed through each tree, which independently processes the features and outputs a class prediction based on the learned splits. In, these predictions from all trees are collected. involves applying **majority voting** across all predicted classes—whichever class receives the most votes becomes the final decision. Finally, in, the classifier outputs this majority-voted **Final-Class**, offering a consensus result that leverages the ensemble's diversity for higher accuracy and reduced overfitting compared to a single decision tree.

## 4. RESULTS

Figure 5 shows a sample output of the dataset uploaded to the Social Media Trend Analyzer. The displayed dataset is a preview of a CSV file containing tweet data, loaded via the uploadDataset function. The table includes columns such as id, keyword, location, text, and target, with five rows of data. Each row represents a tweet, with the text column containing the tweet content (e.g., "Our Deeds are the Reason of this #earthquake M...") and the target column indicating whether the tweet is trending (1) or not (0). The dataset is read using the pandas library and displayed in the GUI's text area using the text.insert method. This preview helps users verify that the uploaded dataset is correctly formatted and contains the necessary fields (text and target) for further processing and analysis.

| | id | keyword | location | text | target |
|---|---|---|---|---|---|
| 0 | 1 | NaN | NaN | Our Deeds are the Reason of this #earthquake M... | 1 |
| 1 | 4 | NaN | NaN | Forest fire near La Ronge Sask. Canada | 1 |
| 2 | 5 | NaN | NaN | All residents asked to 'shelter in place' are ... | 1 |
| 3 | 6 | NaN | NaN | 13,000 people receive #wildfires evacuation or... | 1 |
| 4 | 7 | NaN | NaN | Just got sent this photo from Ruby #Alaska as ... | 1 |

Figure 5. Displays the Upload of Social Media Dataset.

Figure 6 shows the confusion matrix for the RNN-LSTM with Random Forest Classifier (RFC) model, visualized as a heatmap. Generated by the evaluate_model function, the heatmap uses Seaborn and Matplotlib to display the classification performance on the test set (1,523 records). The matrix shows the counts of true positives, true negatives, false positives, and false negatives for the two classes (Class 0: non-trending, Class 1: trending). The axes are labeled as "Predicted" (x-axis) and "Actual" (y-axis), with annotations indicating the number of instances for each combination. The heatmap, rendered in a blue color scheme, provides a clear visual representation of the model's ability to correctly classify tweets, highlighting its high performance as indicated by the evaluation metrics in Figure 5.

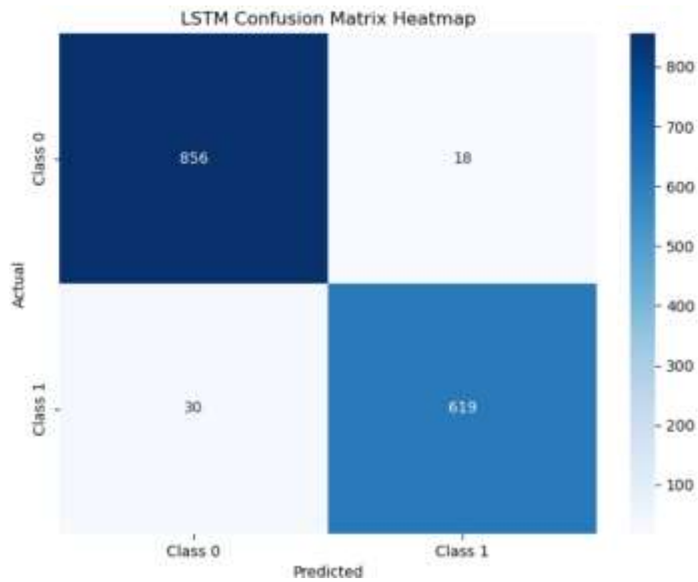


Figure 6. Confusion Matrix of RNN-LSTM with RFC model.

Figure 7 shows the performance evaluation metrics for the RNN-LSTM with RFC model, as computed by the evaluate_model function. The classification report includes precision, recall, and F1-score for each class (0 and 1) and overall metrics. For Class 0 (non-trending, 874 instances), the model achieves 97% precision, 98% recall, and 97% F1-score. For Class 1 (trending, 649 instances), it achieves 97% precision, 95% recall, and 96% F1-score. The overall accuracy is 96.85%, with weighted averages of 96.85% for precision, 96.85% for recall, and 96.84% for F1-score. These metrics are displayed in the GUI text area, indicating the model's strong performance in distinguishing trending from non-trending tweets, with minimal misclassifications.

Figure 8 shows the prediction results for a test dataset processed by the predict function. The output, displayed in the GUI text area, lists seven tweets with their predicted trend status ("TREND" for Class 0 or "NO TREND" for Class 1) using the RNN-LSTM with RFC model. For example, the tweet "Wyrmwood: Road of the Dead (2014) was fucking awesome..." is predicted as "TREND," while "@KellKane thanks I narrowly averted death..." is predicted as "NO TREND." The predictions are based on preprocessing the test tweets using the saved tokenizer, extracting LSTM features, and classifying them with the Random Forest model. This figure demonstrates the system's ability to apply trained models to new data, providing actionable insights into tweet trends.


Figure 8. Prediction From Test Data.

**Table 1. Overall Performance Comparison Table**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| RNN-LSTM with RFC | 96.85 | 96.85 | 96.85 | 96.84 |
| XGBoost | 65.73 | 65.31 | 65.73 | 65.26 |

The table 1 compares the overall performance of the RNN-LSTM with Random Forest Classifier (RFC) and XGBoost models based on the weighted average metrics from Figures 5 and 7. The RNN-LSTM with RFC model significantly outperforms the XGBoost model across all metrics, achieving an accuracy of 96.85% compared to 65.73% for XGBoost. Similarly, the precision, recall, and F1-score for the RNN-LSTM with RFC model are consistently around 96.84–96.85%, indicating high reliability in classifying both trending and non-trending tweets. In contrast, the XGBoost model's metrics hover around 65.26–65.73%, reflecting lower predictive power and more misclassifications. The superior performance of the RNN-LSTM with RFC model is likely due to the LSTM's ability to capture sequential patterns in tweet text, combined with the Random Forest's robustness in handling high-dimensional features extracted from the LSTM. This table highlights the effectiveness of the hybrid deep learning-ensemble approach over the standalone XGBoost model for social media trend prediction.

## 5. CONCLUSION

The proliferation of misinformation in the digital age poses a significant threat to public health, political stability, and social harmony. The rapid dissemination of false information through social media and other online platforms has transformed the landscape of information consumption, where traditional methods of fact-checking and content moderation struggle to keep pace with the speed and scale of misinformation spread. The consequences are profound, affecting individuals' perceptions, decisions, and trust in institutions. In response to this pressing issue, the integration of machine learning techniques into misinformation detection presents a promising avenue for mitigating the impact of false information. By leveraging natural language processing, sentiment analysis, and anomaly detection, machine learning models can efficiently analyze vast datasets, identify patterns indicative of misinformation, and provide timely alerts to users. These automated systems can enhance the efficiency of existing fact-checking efforts, allowing human moderators to focus on nuanced content while machines handle large volumes of data, ethe development of advanced misinformation detection systems will not only help protect public health and democratic integrity but also contribute to restoring trust in digital information ecosystems. As misinformation tactics continue to evolve, it is crucial to adapt and refine machine learning algorithms to address emerging challenges effectively.

In summary, tackling misinformation in the digital age requires a multifaceted approach that combines technology, policy, and public engagement. By harnessing the potential of machine learning, we can create more resilient information ecosystems that empower individuals to navigate the complexities of the digital landscape confidently and responsibly. The commitment to addressing misinformation will ultimately foster a more informed, engaged, and resilient society.

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