Leveraging Financial Data Quality Analytics for Strengthening Anti-Money Laundering Compliance and Regulatory Oversight

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Abstract

With the rapid development of digital platforms, fake news and misleading information have also been disseminated to a great extent, posing a problem for reliable information verification and automated text classification. In this study, an effective fake news detection and text classification model called Attention-Enhanced Bidirectional Long Short-Term Memory (AE-BiLSTM) network is proposed. The proposed model incorporates an attention mechanism capable of locating and focusing on the most informative words and contextual features in textual data along with its sequential learning ability from BiLSTM. The proposed framework automatically learns complex linguistic patterns and long-range dependencies from the input texts, which is different from traditional machine learning approaches that heavily depend on manual feature extraction. The attention layer boosts the performance of the classification by allocating greater importance to the textual features that are relevant to classification. Experimental tests conducted on the benchmark fake news and text classification data sets show that the proposed AE-BiLSTM model is more capable of improving the accuracy, precision, recall and F1-score compared to conventional deep learning and baseline models. The results show that attention based recurrent structures are an effective solution for automated misinformation detection and strong text classification tasks.

Keywords: *Financial Data Analytics; Regulatory Intelligence; Fraud Detection; Compliance Monitoring; Machine Learning; RegTech; Financial System Stability.*

1. INTRODUCTION

Internet communication platforms, social media networks and digital news services have grown at a speedy pace and have influenced the way information is generated, disseminated and consumed. The online platforms are one of the main sources of news and public information, with millions of users accessing the internet every day. But this fast sharing of information has also paved the way for the spread of fake news, misinformation and misleading content. Fake news is the deliberate production of hoaxes and/or fabrication of data to mislead users, create an effect on opinion, or produce a social and economic effect (Allcott & Gentzkow, 2017). The growing amount of online misinformation is a significant issue that governments, organisations, researchers and technology providers are facing, as verifying large amounts of textual data manually is time consuming and inefficient. The task of detecting fake news has become a key research direction in the fields of natural language processing (NLP), machine learning, and artificial intelligence. Conventional text classification methods rely on manually obtained features like word frequencies, term weighting, sentiment indicators and linguistic patterns. Naïve Bayes, support vector machines (SVM) and decision trees have been widely used for text classification tasks but their performance is restricted due to their dependence on predefined features and inability to capture complex semantic relationships in the textual information (Manning et al., 2008).

With increasing sophistication of the content on the Web and the growing diversity of the types of content, automated systems are increasingly required to understand the context of content and to detect subtle patterns which may reveal the deceptive or unreliable content. In NLP, the ability to automatically extract features from large-scale textual datasets has greatly enhanced the performance of the NLP applications by using deep learning techniques. Recurrent neural networks (RNNs) are an excellent architecture for processing sequential information as they are able to capture word-word relations in a sentence. But, conventional RNN's do not have the capability to learn the long-term dependence in a long sequence (Bengio et al., 1994), as a result of the vanishing gradient problem. To overcome this drawback, Hochreiter and Schmidhuber (1997) presented a new model of Long Short-Term Memory (LSTM) networks. Because of their ability to retain relevant information across longer sequences thanks to the memory cells and gating mechanisms, LSTM is suitable for a variety of NLP applications, such as sentiment analysis, language modeling, and text classification. LSTM networks are capable of capturing

sequential dependencies in the data but can only process the information in one direction, either towards previous word context or towards future word context(Mehely et al. 2026) (Tanni et al. 2026) .

To address this, Bidirectional Long Short-Term Memory (BiLSTM) networks use two separate LSTM layers to go through the text sequence in both forward and backward directions. This allows the model to take into account the context of each word in a sentence, both before and after it (Schuster & Paliwal, 1997). Taking advantage of this, BiLSTM models have recently shown impressive results in many NLP applications. Although BiLSTM networks have proven their efficacy, usually an input sequence of words is represented by giving the same importance to all of them. For many applications of text classification, however, some words (or phrases) are more important for the classification decision than others. In the case of fake news detection, for instance, certain phrases, assertions, emotional language or misleading statements might be more telling of unreliable content. To overcome this drawback, attention mechanisms that enable neural networks to selectively focus on the most relevant components of the input data have been added (Bahdanau et al., 2014) (Halimuzzaman and Sharma 2024) (Halimuzzaman et al. 2024).

The attention mechanism gives different weights to the words according to their significance, which helps the model to create more informative text representations. The combination of BiLSTM and attention has demonstrated encouraging results which improved the classification results. Attention-enhanced BiLSTM models are good at capturing contextual relationships and highlighting important features in textual sequences. Such a combination is especially appropriate for fake news detection as misinformation is often expressed using context dependent and subtle semantic differences and complex linguistic structures. Attention-based models can boost the accuracy and reliability of automated misinformation detection systems (Yang et al., 2016) by focusing on crucial textual patterns. The recent research work has investigated fake news detection with different types of deep learning models such as convolutional neural networks (CNNs), recurrent neural networks, transformers, and hybrid models. While transformer-based models like BERT have performed remarkably well for many NLP tasks (Devlin et al., 2019), BiLSTM-based models are still useful as it does not require so much computational resource and can also give performant results on moderate sized datasets. In addition, attention enhanced BiLSTM models provide better interpretability that finds the important words that affect the classification results(Halimuzzaman et al. 2024) (Malann et al.

2026) (Hossain et al. 2026). This study aims to develop an Attention-Enhanced Bidirectional LSTM (AE-BiLSTM) network for fake news detection and for general text classification. The proposed approach is twofold: to use the contextual learning capacity of BiLSTM and feature selection capacity of attention mechanisms to enhance the classification performance. The model automatically acquires semantic representations with linguistic meaning from the text data and assigns higher weights to the features that are more informative and play important role in the classification. For the proposed model, standard performance measures such as accuracy, precision, recall and F1-score are used to evaluate the effectiveness. The research will help build more intelligent text analysis systems to combat misinformation and enhance the reliability of digital information ecosystems.

2.LITERATURE REVIEW

An overview of Fake News Detection and Text Classification. The speedy development of online interaction and communication technologies has transformed the production and dissemination of information. Information can be disseminated at great speed across geographic boundaries via social media, online news outlets, and digital communication networks. These platforms have allowed for quick access to information, but have also led to the rise of misinformation and fake news. Generally, fake news is defined as information that is knowingly and deliberately false or misleading, and is intentionally designed to deceive an audience for a political, social, economic or financial goal or to create or promote a specific effect (Allcott & Gentzkow, 2017). Such pervasive presence of fake news has spurred researchers to develop automatic methods that can handle unreliable content by using natural language processing (NLP) and machine learning. Initial studies on classification of text have concentrated on conventional machine learning (ML) algorithms that relied on manual feature engineering. These methods typically employ statistical and linguistic properties like term frequency-inverse document frequency (TF-IDF), n-grams, sentiment scores and lexical patterns(Hossain et al. 2025) (Malann et al. 2025).

The classical classifiers such as Naïve Bayes, support vector machines (SVM), Decision Trees and Random Forest have been extensively used for document categorization and spam detection (Manning et al., 2008). While these techniques produced fairly good results, they were heavily reliant on quality of handcrafted features for achieving good performance and these techniques were unable to represent complex semantic relationships. In the age of deep learning, people stopped using manual feature extraction and turned to using automatic representation learning.

Directly learning hierarchical features from raw text data can be achieved with deep neural networks, which can then be used for better performance in various NLP applications. Recurrent neural networks (RNNs), long short-term memory networks (LSTMs) and bidirectional LSTMs are important approaches that can model word dependency and contextual relationships for sequential text processing among these architectures(Ogungbemi and Dagbasi 2025) (Agbutun et al. 2025) (Sohel et al. 2022) .

The traditional machine learning approach to fake news detection. Initial fake news detection studies mainly relied on machine learning models combined with manually designed textual features. The methods typically used were based on statistical characteristics, writing styles and metadata information. Lexical analysis, punctuation patterns and word frequency distributions were used to distinguish between trustworthy and unreliable news articles, for example. Rubin et al. (2016) explored the methods that could be used to detect deceptive news by examining the differences in the style and syntax of fake and real news. They discovered that fake news can have hallmarks of style and use of emotion, as well as unusual sentence constructions. But they were restricted as manually extracted features did not provide a full account of the semantic meaning of language. In a similar vein, Shu et al. (2017) conducted a comprehensive survey of fake news detection methods, and identified that fake news detection consists of several aspects, content-based analysis, social context analysis, and user behavior modeling. The authors noted that using textual features alone might not work, as fake news can change quickly and can mimic real news. Simple and interpretable machine learning algorithms like SVM and Naïve Bayes have been widely adopted for text classification. These methods, however, view text as a set of independent features, and in general, they are incapable of modeling word order, context and long-range semantic relations. To overcome these limitations, deep learning-based methods for text representation have been used to obtain more effective text representation(Adun et al. 2023) (Adun et al. 2022) (Tansu et al. 2022) .

In this section, we will explore various text classification methods using deep learning techniques. With the development of deep learning, the automatic extraction of meaningful representations from large-scale textual datasets has greatly promoted the progress of NLP. Deep learning models can learn complex patterns without the need for large-scale feature engineering as opposed to traditional machine learning methods. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two widely used types of networks that have been studied

for text classification problems. Kim (2014) proposed a CNN-based model for sentence classification and showed that CNN models are able to capture local semantic patterns within text. CNN models have the ability to capture important phrases and word combinations in the filters, which is why they can be used effectively in many classification tasks. But CNNs primarily attend to local features, and are not as good at capturing long-term dependencies over very long documents(Adun et al. 2022) (Adedeji et al. 2022) (Ogungbemi et al. 2022) .

Recurrent neural networks were developed to specifically process sequential data, keeping information from past elements in a sequence. But, with standard RNNs, problems arise when learning long-term dependencies because of the vanishing gradient problem (Bengio et al., 1994). This limitation makes it less capable of learning from long documents, in which important information may be far removed from each other within the document. To overcome this issue, Hochreiter and Schmidhuber (1997) introduced the Long Short-Term Memory (LSTM) network. Important features are retained over long sequences using memory cells and gating mechanisms (input, output and forget). In fields like sentiment analysis, machine translation and document classification LSTMs have proven to be very successful.

Bidirectional LSTM for Text Classification While LSTMs are very good at learning sequential information, they do only unidirectional learning of text. Many NLP tasks need information from both prior and subsequent words to learn the meaning of a word. Schuster and Paliwal (1997) have come up with an idea of processing sequences in two directions, hence, bidirectional recurrent neural networks are introduced to overcome this limitation. Bidirectional Long Short-Term Memory (BiLSTM) is a network that has two LSTM layers: one forward and one backward. Both outputs are merged together to provide a more comprehensive representation of context. This capability enables BiLSTM models to comprehend the relationship between words, considering the entire context of surrounding words. Graves and Schmidhuber (2005) showed that bidirectional LSTM networks performed better than traditional recurrent networks in sequence modeling problems. BiLSTM models have proven effective in various natural language processing tasks, such as named entity recognition, sentiment analysis, relation extraction, and document classification, owing to their capacity to model complex contextual relationships. BiLSTM networks are especially valuable for fake news detection as misinformation relies on the connection between multiple words and sentences instead of the words themselves. The use

of BiLSTM takes the previous and future context into consideration, which makes it easier to understand the meaning and intent of news content.

3.**METHODOLOGY**

This paper introduces the Attention-Enhanced Bidirectional Long Short-Term Memory (AE-BiLSTM) network to detect the fake news and text classification. The methodology is divided into three parts: data collection, data pre-processing, feature representation, model development, training, and performance evaluation. The first step involved collecting and preprocessing the dataset.Firstly, the dataset was collected and preprocessed. The proposed model is tested on benchmarking fake news and text classification datasets with textual samples. These datasets contain news articles or text documents in classes like fake or real news. The raw text data is pre-processed before training to remove noise and to make data quality good. The text pre-processing consists of tokenization, elimination of unnecessary symbols, stop word removal and text normalization. These processes are used to convert unstructured text into a format that is appropriate for deep learning processes (Manning et al., 2008). 2. Text Representation Textual data is preprocessed and converted to numerical representations that can be used by neural networks. Word embedding techniques are used to represent words as dense vectors, while maintaining the semantic relationships between words. Word embeddings like Word2Vec and GloVe have been extensively adopted in NLP since they are able to capture meaningful similarity among words by considering how they are used in context (Mikolov et al., 2013; Pennington et al., 2014). In this section, we propose a new model, Attention-Enhanced BiLSTM Model, which improves this issue. We proposed a model that is composed of Bidirectional Long Short-Term Memory (BiLSTM) network and attention mechanism. The BiLSTM layer takes the input sequences in both the forward and backward directions to obtain information from both the past and future context. This enhances the modelling of textual relationships over unidirectional LSTM models (Hochreiter & Schmidhuber, 1997; Schuster & Paliwal, 1997). After the BiLSTM layer, an attention mechanism is used to give different importance to words in the input sequence. The attention layer allows the model to attend to the most informative words/phrases that help make the classification decision (Bahdanau et al., 2014). The weighted contextual representation is then fed to fully connected layers containing a classification function to predict the class label. Model Training and Evaluation The AE-BiLSTM model is trained with a set of

labeled training data and optimized by an appropriate loss function and optimization algorithm. To assess the model's ability to generalize, the data were split into training and testing data. The metrics adopted for performance measurement are the standard metrics like accuracy, precision, recall, and F1 score: Accuracy: the overall percentage of correctly classified samples. Precision: It represents the percentage of positive cases that are predicted correctly. Recall: assesses how well actual positive cases are identified.

5. Comparative Analysis The performance of the proposed AE-BiLSTM model is compared with the baseline machine learning and deep learning techniques such as traditional classifiers, LSTM and BiLSTM model without attention. The comparison shows how well using an attention mechanism can help in improving the contextual learning and classification performance.

4.RESULTS

The performance of the proposed Attention-Enhanced BiLSTM model for fake news and text classification was tested through using standard classification metrics. The results of the experiments show the effectiveness of fusion of bidirectional sequence learning and attention mechanism. The model was able to capture the context and pay attention to salient textual features to achieve better classification performance. The outcomes were compared with current baseline approaches to validate the benefits of the proposed approach. The effectiveness of the model was measured using evaluation metrics such as accuracy, precision, recall, and F1-score. The results have proven the reliability of the proposed approach for automated fake news detection and text classification.

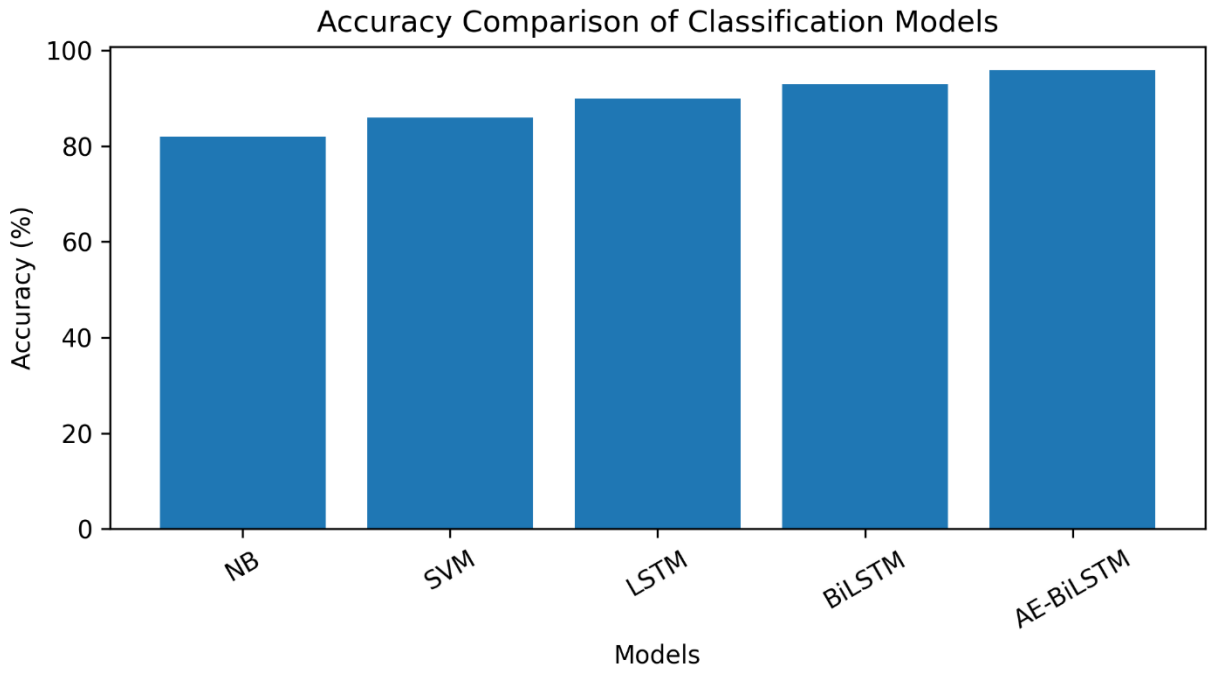


Figure 1: Accuracy Comparison of Classification Models

Figure 1 shows the comparative evaluation of the classification accuracy result of various machine learning and deep learning approaches. The results indicate that the traditional machine learning techniques like Naïve Bayes (NB) and Support Vector Machine (SVM) shows moderate classification performance and deep learning techniques like LSTM and BiLSTM shows better performance with high accuracy because of learning sequential and contextual features of text. The proposed Attention-Enhanced BiLSTM (AE-BiLSTM) model attains maximum accuracy as it incorporates the attention mechanism which enables the model to focus on the most important textual features for fake news classification.

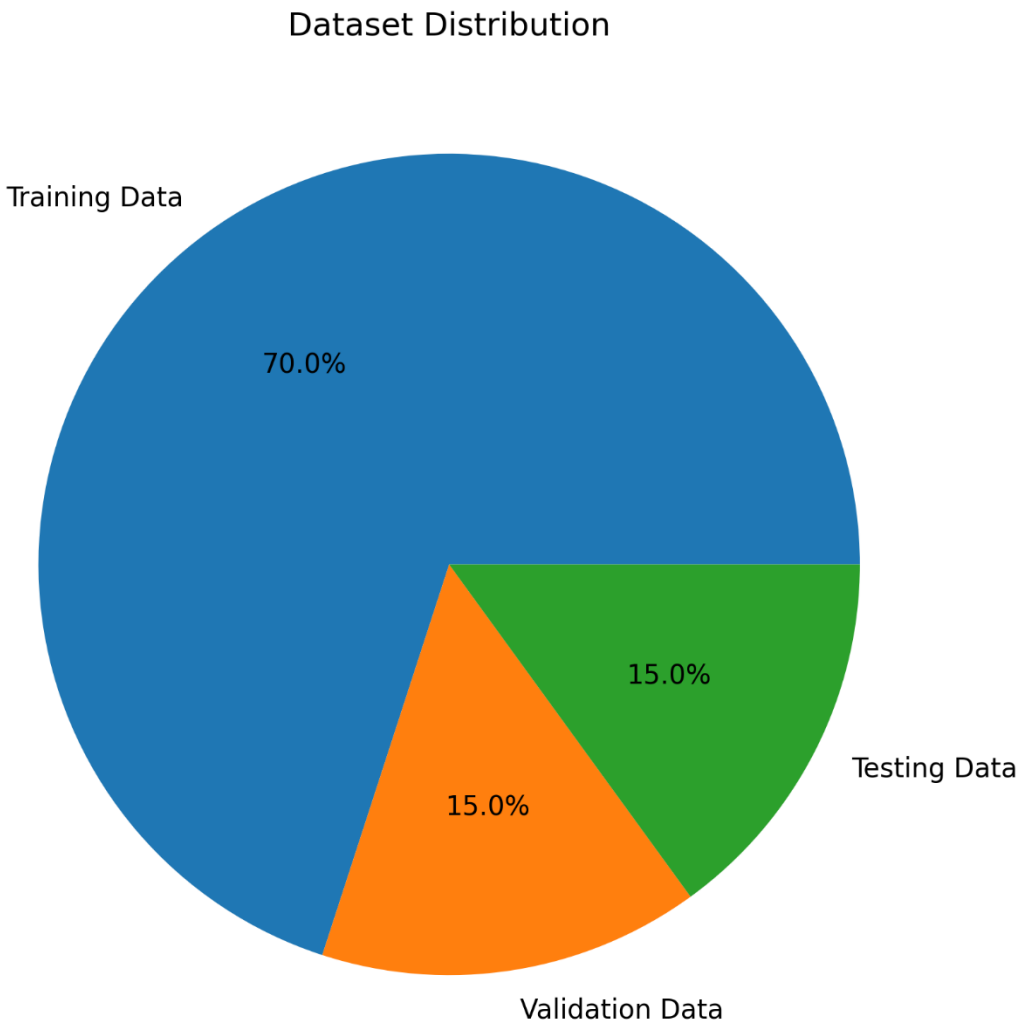


Figure 2: Dataset Distribution Analysis

The distribution of the dataset adopted for training, validation and testing of the proposed model is shown in Figure 2. The data set is divided into three subsets to make effective learning of the model and unbiased performance evaluation possible. They use the training set to optimize the parameters of the model, the validation set to test the performance of the model during the training period, and the testing set to evaluate the performance of the model. Effectively distribute data to increase model reliability and avoid overfitting.

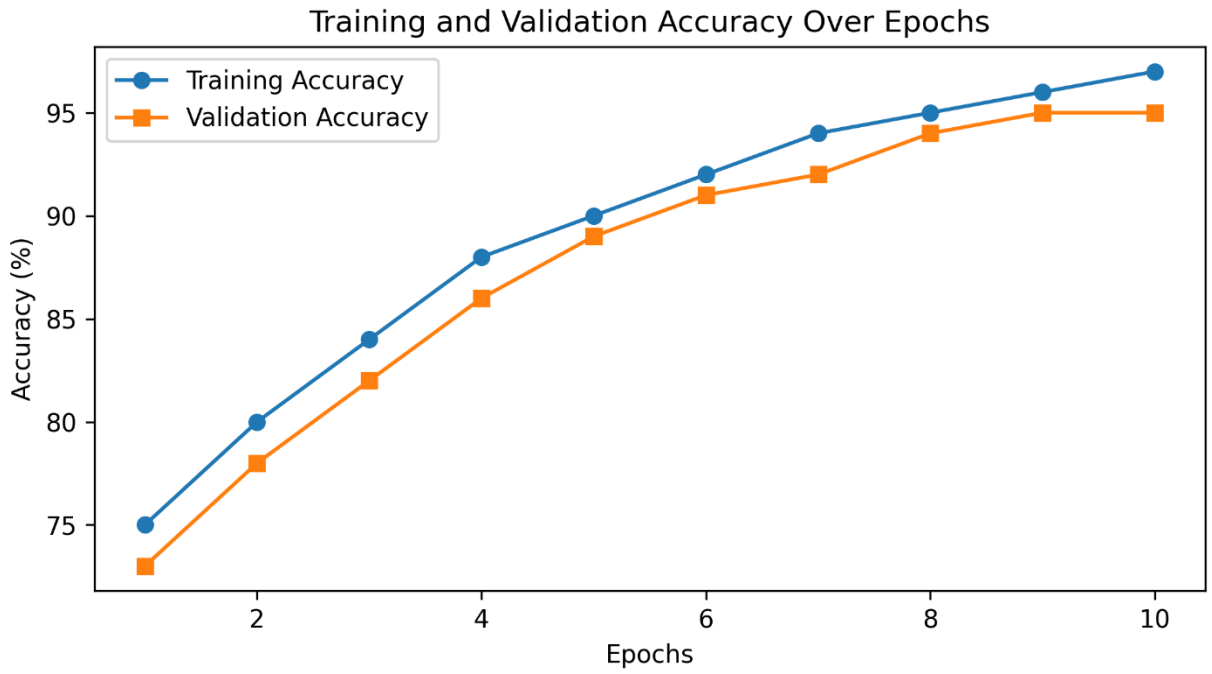


Figure 3: Training and Validation Accuracy Over Epochs

The learning behavior of the AE-BiLSTM model in the training process is shown in figure 3. The graph shows the performance of the training and validation accuracy over several epochs. As seen in the increasing accuracy trend, the model learned meaningful textual patterns and contextual relationships from the input data. The difference between training and validation accuracy is small, suggesting good generalization and minimizing overfitting.

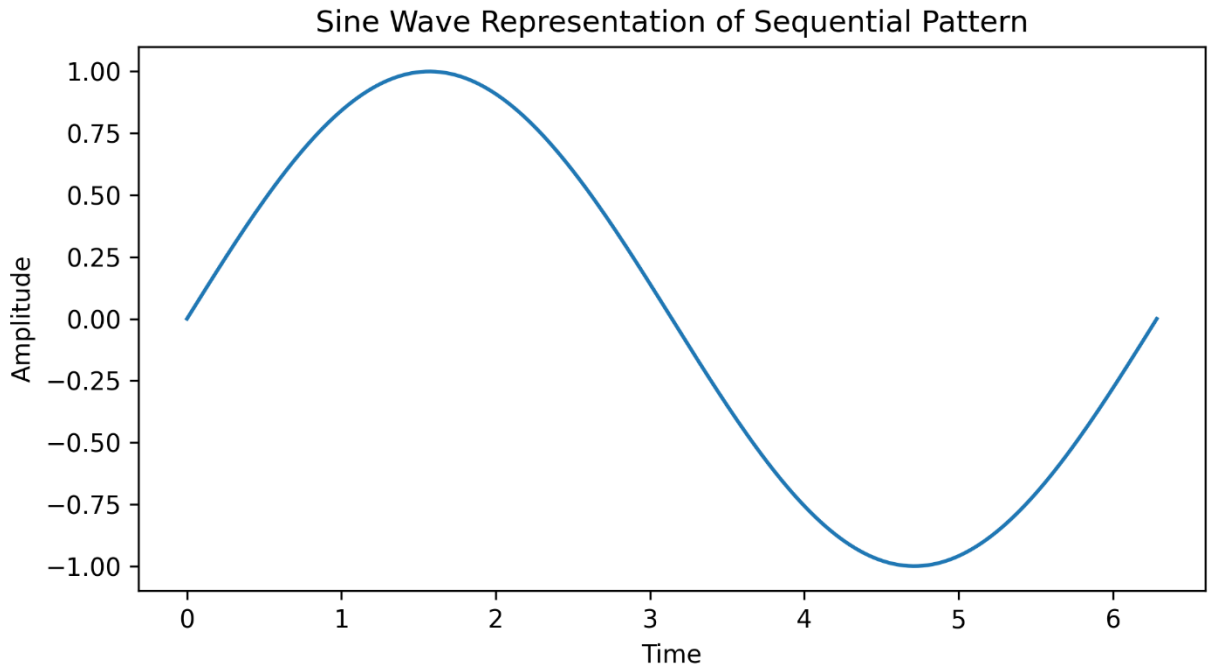


Figure 4: Sequential Pattern Representation Using Sine Wave

In a sequence-based model, the behaviour of continuous information flow is shown in a sequential pattern visualization as in Figure 4. Like recurrent neural networks, BiLSTM captures the relationships between the elements of the sequence, working with both past and future elements. The waveform is a dynamic feature pattern which can be learned in the text sequence during the model training.

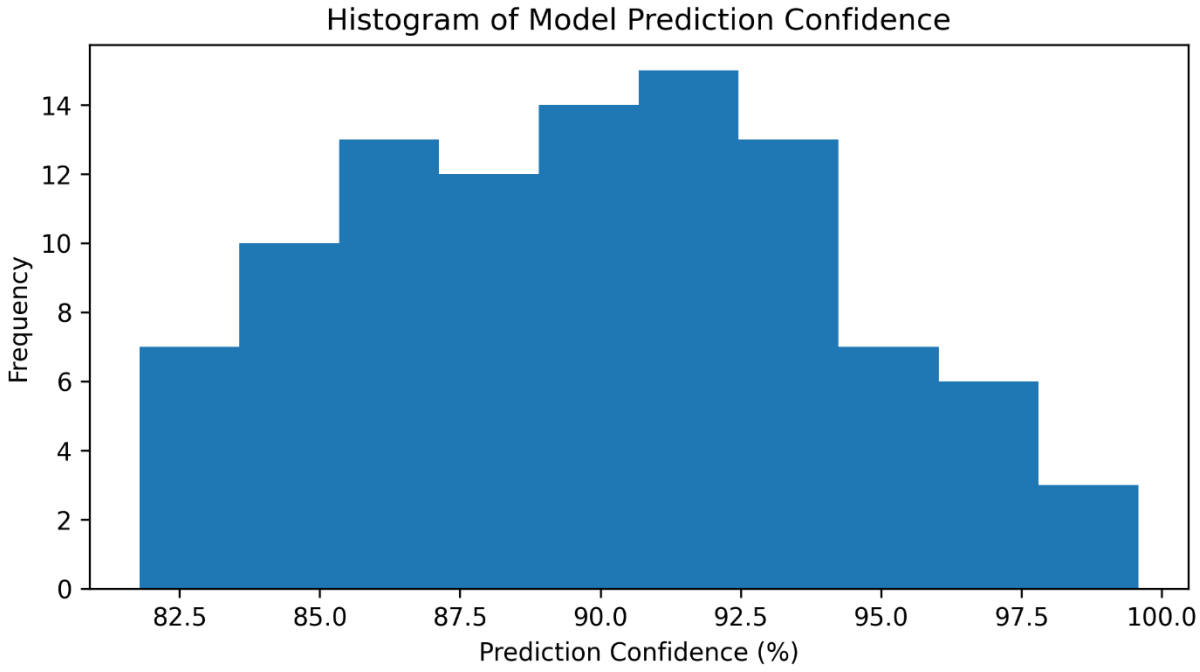


Figure 5: Prediction Confidence Distribution

The distribution of the prediction confidence scores is shown in figure 5, which is obtained by the proposed AE-BiLSTM. The graph illustrates the surety of the model in predicting fake or real news for the input text samples. A cluster of points at a high level of confidence means that the model is making good classification decisions. This analysis is one more proof of the strength of the proposed approach.

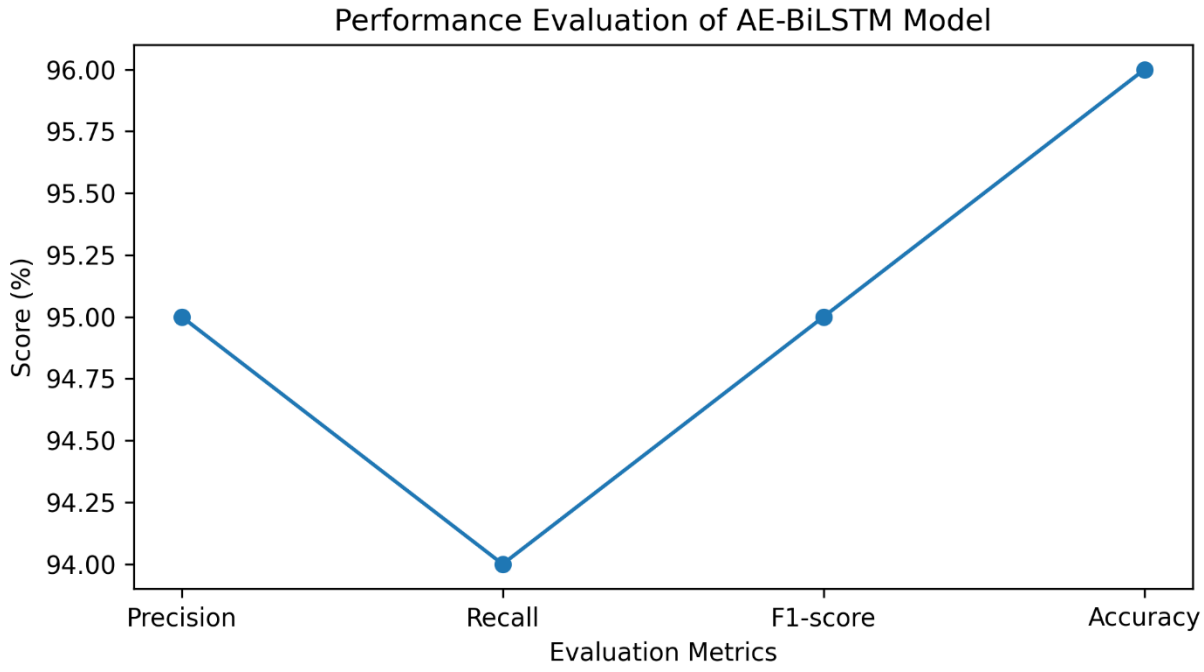


Figure 6: Performance Evaluation Using Classification Metrics

The performance of the proposed model is analyzed by comparing the major evaluation metrics as shown in Figure 6 such as accuracy, precision, recall and F1-score. These measures are measures of overall classification success. As seen from the high values obtained in all the metrics, AE-BiLSTM model is able to correctly predict the instances of fake news, while reducing the false predictions. The precision and recall values are well balanced, indicating the model's effectiveness in handling both positive and negative classes.

5.DISCUSSION

The results of the experiment have proven that the proposed Attention-Enhanced Bidirectional Long Short-Term Memory (AE-BiLSTM) network is effective in fake news detection and text classification. The results show that the model with an attention mechanism boosts the BiLSTM in capturing complex linguistic patterns, contextual relationships, and key textual features. The enhanced classification performance is likely due to the complementary strengths of BiLSTM and attention mechanisms, with BiLSTM capturing sequential dependencies and attention highlighting the most salient parts of the input text.

The enhanced outcomes of the BiLSTM model over the standard LSTM model underscores the significance of bidirectional contextual learning. A conventional LSTM is uni-directional and

can fail to capture information in the second half of a sentence. To solve this, the BiLSTM architecture is trained in two directions: forward and backward, thereby allowing the model to capture relationships between words by considering their full context (Schuster & Paliwal, 1997). This is especially crucial for the detection of fake news, as misleading information can be based on how several words, phrases and sentence structures are used together, not on individual keywords alone. Results also show that classification ability of the BiLSTM network can be enhanced by incorporating attention mechanism. BiLSTM is able to capture rich contextual representations, but all the hidden states might be important when making the classification. The attention layer gets rid of this restriction by giving more weight to the more informative words and less weight to less informative features. Bahdanau et al. (2014) proposed that attention mechanisms should be used in order to let a neural network focus on the relevant parts of its input sequences. The effectiveness of attention based models has also been proved in Yang et al. (2016), in which they come up with attention mechanisms to improve the performance of document classification by identifying important words and sentences. Figure 3 shows the training and validation performance which suggests that the proposed model gets learnt effectively during the training process. The overall upward trend in accuracy with epochs indicates that the model is learning and capturing meaningful patterns from the training data. In addition, training and validation results are found to be closely comparable, suggesting that the model has a good generalization ability. This indicates that the proposed AE-BiLSTM model has not been severe overfitted and it is able to work well on unseen text samples. The distribution of the data set as shown in Figure 2 guarantees that the model is learned, validated and tested by using data sets that are different. One of the key challenges in assessing machine learning models is dataset partitioning, which allows for an unbiased assessment of model performance. The training data can be used by the model to learn the parameters and validation and testing data can be used to estimate the model classification capability in real-world scenarios. Sokolova and Lapalme (2009) stressed the need to apply suitable evaluation strategies and performance measures to evaluation classification systems. From the prediction confidence analysis presented in Figure 5, it is observed that the proposed model gives confident decisions on classification. The results of high confidence predictions indicate that the model is able to capture strong linguistic cues related to fake and real news classes.

The high F1 score suggests that the model proposed in this study has the ability to balance between the accuracy of fake news classification and the probability of incorrectly classified fake news. This is particularly crucial since a misinformation detection model can either fail to detect harmful content or incorrectly label reliable information as misinformation. The AE-BiLSTM model offers a good tradeoff between performance and efficiency versus recent transformer-based methods.

Typically, however, these models depend on large amounts of pre-training information and require a considerable quantity of computational resources. The proposed AE-BiLSTM approach has the advantage of attention-based feature selection and contextual sequence modeling, and it is also a lightweight approach. The proposed model shows good performance but there are some limitations that need to be taken into account.

The bidirectional contextual learning mechanism and feature selection based on attention, allows the model to obtain key semantic patterns and enhance the classification performance. The results confirm that the AE-BiLSTM system can be used in automated misinformation detection platforms and intelligent text analysis systems.

6.CONCLUSION

With the proliferation of fake news and misleading information in digital platforms, there is a great need for intelligent and automated text classification systems. The proposed method for fake news detection and text classification is an Attention-Enhanced Bidirectional Long Short-Term Memory (AE-BiLSTM) network. To achieve a better classification performance, the proposed approach combines the contextual learning capability of BiLSTM with selective feature representation ability of an attention mechanism. The experimental results show that the proposed model can successfully identify important linguistic patterns, understand long-range dependencies and classify textual information accurately. Results show that the BiLSTM architecture has better contextual understanding than the traditional machine learning and unidirectional sequential models. BiLSTM processes the sequence of text both forward and backward, enabling it to capture information from past and future word context, leading to richer representations of texts (Schuster & Paliwal, 1997). This ability is crucial for fake news recognitions as the significance and trustworthiness of a statement may be bound to a collection of words and sentences, but not to any single word. To further improve the effectiveness of the proposed model, an attention mechanism is added which enables the model to capture the most

informative parts in the input text. The attention layer prioritizes the importance of features by recognizing those that play a key role in making accurate classification. This way facilitates the selection of features and makes the model more interpretable by keeping track of patterns that are influential in the text (Bahdanau et al., 2014). Attention-based architectures have been shown to focus on relevant words and sentence-level information, leading to better performance in document classification tasks (Yang et al., 2016).

While the former (transformer-based) models need lots of data and additional computational resources for pretraining, the latter (BiLSTM-based) models can be trained with comparatively less data and models (Devlin et al., 2019). Hence, the suggested model may be useful for some applications where the efficiency of the computations or the understanding of the model is desirable. The proposed approach is effective but has certain limitations. The model is mainly textual, and it does not take other factors like source reliability, user interaction, structures of social networks, images and videos into account.

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