RESEARCH ARTICLE OPEN ACCESS

Dealing with fake news on social media

Riham Kherbek [1], Ebrahim Massrie [2]

Master in Web Science, Syrian Virtual University Faculty of Information Tech, and Latakia, Syria

Faculty of Information Tech, Damascus University Faculty of Information Tech, and Latakia, Syria

ABSTRACT

This paper is aimed at fake news propagation on social media, developing a model based on artificial intelligence techniques to accurately detect such news. It utilized the ISOT dataset from Kaggle, which consists of long articles with corresponding English headlines and classified into two categories: "True" and "Fake." The balanced nature of this dataset ensures that the model does not exhibit bias towards any category. The model was built on State Space Models, specifically the Mamba 130m model, which is known for its efficiency and low computational resources consumption compared to other models within the category. The initial phases of the processes were primarily data cleaning and analysis, before numerical conversions of the text through encoding techniques and tokenization. The dataset was then split into 80% for training, 10% for validation, and 10% for testing. The results showed that the developed model achieved a notable level of accuracy on the test set overall, at 99.83%, with precision, recall, and F1-Score values approaching perfection both for true and fake news categories. Such performances affirm that the model can reliably separate a real from a false news, hence would provide a robust novel tool for combating misinformation in real-world applications. This actually constitutes the very first use of the Mamba 130m model for fake news detection, thus contributing as a new dimension to the area. The remarkable results set the stage for future endeavors aimed at developing even more effective models to combat online misinformation.

Keywords — Fake news detection, Transformer models, Text classification, Natural Language Processing, Content-aware models, Mamba.

I. INTRODUCTION

Social networking sites have developed to become huge data repositories of information, providing their users with unparalleled opportunities to share their ideas, beliefs, and ideologies [1], [2]. This openness, however, is not without some dangers, among which is the propagation of misinformation. Misinformation usually comes in a way that seems credible and reliable, hence making it very hard for one to distinguish between incorrect information and genuine content [3]. The vast circulation of fake news carries a far-reaching impact on society because it shapes how the government, organizations, and individuals are responding to events. Targeting specific demographics, fake news serves the purpose to polarize communities by provoking intensive beliefs and strengthening ideologies [4].

The rapid spread of disinformation has a considerable impact on societal trust, public discourse, and decision-making processes, hence causing significant dangers to social cohesion, institutional trust, and the stability of democratic systems. Systematic fact-checking and rating of web content can prevent conflicts and social unrest [3], [5], [6]. Although substantial investment has been made in state-of-the-art fact checking approaches, including Adobe's "Content Authentication" initiative for detecting manipulations of content, the challenges remain. Disinformation is growing in popularity, where users often engage, support, or share false narratives. This persistence may be due to the discrepancy between fact-checking tools and users' central beliefs, which does not allow people to embrace such solutions fully [7].

Misinformation identification has thus become a key area of research. Traditional methods have often struggled to keep up with the dynamic nature of misinformation, which more and more leverages technological advancements to become almost indistinguishable from real content. There is, therefore, a great need for new and scalable methods that can efficiently detect misinformation. Recent advances in NLP and machine learning have provided strong tools to deal with the problem. Transformer-based models, such as BERT and GPT, have shown extraordinary effectiveness in text classification tasks because of their ability to deeply understand complex linguistic structures.

However, such models face some limitations, in particular, the computational inefficiency due to their quadratic time complexity in analyzing large datasets [8].

In the face of such challenges, Selective State-Space Models (SSMs) [9] have emerged as feasible alternatives for sequential data management. These models are designed to effectively distinguish patterns in textual sequences and are remarkably efficient and robust in their performance, as evidenced through text classification evaluations. Among these, the Mamba model has been noted in several studies for its architectural benefits and its ability to process textual information with remarkable efficacy. Despite the potential, SSM applications, including Mamba [10], to fake news detection remain underexplored—a very important gap in using such models toward the challenges of disinformation. In an effort to bridge this gap, this work proposes a novel methodology for fake news detection using the state-of-the-art Mamba state-space model. The approach that is suggested here is to make the Mamba model refined with content-sensitive parameters so that it has its ability improved in capturing the nuances of classification of fake news. Building on the efficiency and adaptability of SSMs, this work seeks to overcome the computational challenges of traditional Transformer-based models by offering a more robust and accurate solution in detecting deceptive narratives within textual data. This study contributes to the fast-growing field of misinformation detection, proposing an advanced methodology that could strengthen current efforts in battling the spread of false information in a constantly changing digital environment.

The main contributions of this paper are as follows:

- Application of Mamba to Fake News Detection: This is a proof that the Mamba model with its selective state-space can be adapted for fake news detection in texts as well.
- Performance Assessment Using a Single Dataset: Assessing the performance of Mamba on one of the famous benchmark fake news datasets, checking its accuracy and robustness in classifying genuine and misleading information.
- Efficiency-Accuracy Exploration: Demonstrate Mamba's capability of achieving high classification accuracy with minimum computational complexity, hence making it a feasible and efficient choice for fake news detection.
- Comparative Study with Transformers: Comparing Mamba's performance with traditional transformer-based models to highlight its advantages in accuracy and computational efficiency for fake news detection.

The structure of this paper is outlined as follows. In Section II, the background and related literature on the detection of fake news are discussed. Section III describes our methodology using Mamba for fake news detection. Section IV gives a detailed overview of the datasets used for this paper. Section V explains the experimental results in detail. Finally, Section VI concludes the paper and provides ideas on where further research could be pursued.

II. BACKGROUND AND RELATED WORK

The broader study of the identification and classification of false information falls under the scope of Natural Language Processing (NLP), which applies different methods ranging from lexical and syntactic analysis to more advanced approaches of deep learning like transformers and large language models. Researchers in this domain have found machine learning (ML) and deep learning techniques effective in analyzing and identifying fake news articles [11]. This work proposes a new approach by resorting to the use of state-space models, which have a different architecture than transformers but have shown benefits in several tasks. This investigation tries to assess their capability in enhancing accuracy for fake news detection [12].

Social media sites have hastened the spread of news, making them a two-edged sword: while they provide easy access to information, they also lead to the rampant circulation of inferior or even manipulative information [12]. The pernicious consequences of misinformation have motivated a high volume of scholarly research into detection strategies, which integrate linguistic features with additional data in order to enhance decision-making, since sole approaches often fail to reach the desired accuracy level [12].

Text classification is a core NLP task, which involves assigning one or more labels to a text from a predefined set of labels [13]. In the area of fake news detection, text classification is applied to classify news articles into classes like "true" or "fake." When machine learning is applied in text classification, it brings efficiency and scalability compared to human expert labeling, but it still has a big problem with interpretability. Although traditional machine learning methods are still widely adopted, deep learning models, in particular Transformers, have been dominating the area recently. However, Transformers suffer from issues of computational inefficiencies [14].

Alternatives are the Selective State-Space Models, such as Mamba [10], which have been shown to be quite faster and powerful for text classification tasks. SSMs [15] have good properties for modeling sequential data and also prove to be beneficial in some NLP tasks, such as fake news detection, where they outweigh Transformers in terms of efficiency and scalability. This paper tries to apply SSMs, particularly Mamba, to the task of fake news detection in order to outline their potential in overcoming the limits of Transformer-based models and suggesting a solution with better accuracy and computation efficiency in fake news identification.

Before discussing the use of Transformers [16] and State Space Models in detecting false information, it is helpful to evaluate how traditional machine learning compares against modern deep learning architectures like BERT [14] and Mamba [10]. Such a comparison, shown in Table 1, demonstrates that Mamba and other SSM-based models outperform Transformers in some specific natural language processing (NLP) tasks, especially those requiring analyzing long sequences of text, such as the task of fake news detection.

The following sections will explore the use of modern methodologies, specifically Transformers and State-Space Models, in the domain of fake news detection, analyzing how these methods diverge from their predecessors on the axes of performance, efficiency, and interpretability.

TABLE 1 COMPARISON BETWEEN MAMBA AND TRANSFORMERS

Model / Specifications	Transformers	Mamba
Architecture	attention-based	SSM-based
Complexity	Higher	Lower
Inference Speed Complexity	$O(n)$	$O(1)$
Training Speed	$O(n^2)$	$O(n)$

A. *Sequence Models*

Deep Learning and Sequence Modeling are closely related concepts in the field of artificial intelligence [17], where each is used to enhance the other's performance in processing sequential data such as texts, speech, and time series [18]. Sequence models are a type of model used to process data that comes in a sequential form [9], where each element depends on previous ones. The relationship between Deep Learning and Sequence Models can be summarized as follows:

1) RNNS

RNNs are a type of neural network primarily used in sequence modeling [19]. They rely on internal loops that allow them to process sequential data by retaining previous state information and using it in current computations. RNNs are used in various applications such as machine translation, speech recognition, and text generation.

The key feature of RNNs is the presence of internal loops that allow information to be passed from one time step to the next within the network. This enables them to retain memory of previous inputs when processing new ones, making them suitable for tasks such as speech recognition, machine translation, and natural language processing (NLP) [19].

2) Long Short-Term Memory Networks

LSTMs are an improvement over traditional RNNs [20], designed to overcome the vanishing and exploding gradient problem that hinders RNNs from learning long sequences. LSTMs achieve this through specialized memory units that enable them to retain information over longer periods.

3) Transformers

Transformers [18] have become the gold standard in sequence processing. They rely on an "attention mechanism" that allows the model to focus on different parts of the sequence dynamically, enabling it to better handle long-range dependencies in sequential data. Models like BERT [21] and GPT are prominent examples of using transformers for natural language processing.

B. Machine Learning in Fake News Detection

Machine learning (ML) has emerged as a pivotal tool in detecting fake news, leveraging high-quality big data analytics alongside technologies such as AI, fact-checking tools, neural networks, and new media literacy [11]. Hybrid approaches, like the one proposed by Seddari et al. [22], combine linguistic features (e.g., sentiment, lexical diversity) with fact-verification attributes (e.g., platform reputation, source credibility), achieving notable accuracy (REC=97.90, F1=94.90, ACC=94.40) using Random Forest. Similarly, Jain et al. [23] introduced "ConFake," a feature-enriched model that integrates word embeddings with linguistic features, demonstrating high performance (ACC=97.31%, F1=97%) on a dataset of over 72,000 articles. However, both approaches face limitations, including reliance on textual data and constrained generalization across diverse modalities. Park et al. addressed these gaps by incorporating user attributes, social network metrics, and textual properties in a social media contextual model, achieving up to 96.7% accuracy with models like CART and NNET. While generative AI introduces the risk of sophisticated fake content, it also serves as a robust tool for mitigating misinformation. This research builds on these foundations by exploring state-space models, which promise to enhance detection accuracy and establish a more reliable framework for combating fake news in digital ecosystems.

C. DL in Fake News Detection

Despite advancements in AI, detecting fake news remains challenging due to the lack of accurate datasets, traditional verification methods, and the heterogeneous nature of digital content [24], [25]. Deep learning models have proven effective in addressing these challenges, utilizing techniques like NLP, user behavior analysis, and propagation modeling to classify news authenticity. Allein et al. proposed an ethical detection algorithm avoiding user profiling while leveraging social and textual contexts using cross-modal loss functions, achieving superior accuracy with CNN, HAN, and DBERT models [26]. Ni et al. introduced Multi-View Attention Networks, combining text semantics and propagation structure analysis for early fake news detection, yielding high accuracy and interpretability [27]. Amer et al. utilized contextual linguistic features with deep learning, showing BERT's superiority (99% accuracy) over other methods [28]. Kaliyar et al. developed DeepFakE, combining content, social context, and echo chambers for detection, achieving 85.86% accuracy on BuzzFeed and 88.64% on PolitiFact datasets [28]. Su et al. proposed Us-DeFake, integrating multi-relational user-news interactions with dual-layer graph neural networks, which outperformed traditional methods with 96.7% accuracy on PolitiFact and 95.4% on GossipCop [28].

D. text Classification in state space model

State Space Models (SSMs) assume that dynamic systems, such as an object moving in 3D space, can be predicted from its state at time t through two equations. The state-space model is characterized by the following equations, which map the one-dimensional continuous input signal u(t) to an N-dimensional hidden state x(t). The hidden state is then projected to a one-dimensional output y(t) [10].

The state equation is given as follows:

$$x'(t) = Ax(t) + Bu(t) \tag{1}$$

Where the output equation is given as follows:

$$y(t) = Cx(t) + Du(t) \tag{2}$$

where, *A*, *B*, *C*, and *D* represent trainable parameters. A discrete sequence, such as text, can be conceptualized as discretized data sampled from a continuous signal with a step size Δ. The corresponding state-space model in a recurrent manner is given as follows:

$$hk = \bar{A} h_{k-1} + \bar{B} x_k \tag{3}$$

$$yk = \bar{C} h_k + \bar{D} x_k \tag{4}$$

$$\bar{A} = (^{I} - {}^{\Delta}/_{2.A})^{-1} + (^{I} + {}^{\Delta}/_{2.A}) \tag{5}$$

where $\bar{A}$ is the discretized state matrix and $\bar{B}$, $\bar{C}$, and $\bar{D}$ share the similar formulas [29].

To enrich the state space models, the selective approach imbues it with the capability to select the attendant inputs, either retaining or disregarding the SSMs based on their contextual relevance. By incorporating this selective mechanism, the state space model has gained precise ability to adapt its processing according to the specifications of the input sequence [30]. Consequently, the selective approach is able to handle tasks that demand dynamic attention allocation, such as Selective Copying and Induction Heads. This improvement over the conventional state space model has enabled more refined and context-aware processing, enhancing the model's performance across a range of sequential data tasks [10].

Mamba architecture is a simplified yet powerful design for selective state space models (SSMs) within neural networks. Inspired by the H3 architecture [10], which has formed the foundation of many SSM architectures, Mamba block combines elements of linear attention with an MLP block in a homogeneous stack as shown in Fig. 1. Unlike traditional approaches that interleave these components, Mamba block repeats a unified structure, replacing the first multiplicative gate with an activation function and integrating an SSM into the main branch. This design choice allows for dynamic adaptation to input sequences while maintaining computational efficiency. With a controllable expansion factor E, Mamba architecture expands the model dimension while keeping the number of the SSM parameters relatively small compared to linear projections. By stacking Mamba block and incorporating standard normalization and residual connections, the architecture achieves robust performance across various tasks. Additionally, the use of SiLU/Swish activation functions and optional normalization layers further enhances the adaptability and efficiency of the Mamba architecture, making it a versatile tool for sequential data processing tasks [10].

SSMs have shown remarkable performance in text classification, particularly with long documents [9]. For example, studies have demonstrated that SSM models, including S4, S4-pooler, Longformer, and H3, outperform self-attention models like Transformers in both performance and training efficiency. These models excelled in classifying datasets such as ECtHR, Hyperpartisan, 20News, EURLEX, and Amazon product reviews [10], [29]. The improved performance of SSMs, combined with reduced training time, underscores their potential for applications like fake news detection, especially in handling lengthy textual inputs efficiently. Further research into architectures like Mamba could unlock their full potential in this domain.

III. METHODOLOGY

This work investigates how the Mamba architecture performs in sequence modeling tasks, using the smallest pre-trained Mamba model mamba-130m as the classification solution. The model can create remarkable equilibrium between executing tasks and the corresponding costs, thus, it can deal with the sequence as large as a million elements without the needed step of either partition or curtailment. The EleutherAI/pythia-160m tokenizer is employed for text tokenization. Here, we review our Mamba-130m classifier including the Mamba-130m model, the tokenizer settings, and the conceptualization of our Mamba-130m classifier.

This study probes the Mamba architecture for sequence modeling tasks with the smallest pre-trained Mamba model, mamba-130m, which is the bedrock of our classifier. The model exhibits an excellent performance-efficiency ratio, which allows it to process sequences of up to 1 million elements in full and without cuts. The EleutherAI/pythia-160m tokenizer is used for text tokenization. In the next paragraph, we are going to discuss the mamba-130m model, the tokenizer, and the Mamba-130m classifier construction.

E. Mamba-130m

Mamba is a space-time model of spatial and temporal data. It includes a language modeling tasks where previous quadratic approaches failed. Transformers were hidden behind other models. Based on the development of structured state-space models, Mamba has a novel hardware-oriented architecture that is reminiscent of Flash Attention [8]. The following are its noteworthy features:

- High Quality: Dedicated state-space mechanisms guarantee the best results in dense modalities like language and genetics.
- High speed of learning and inference: Computation and memory scales in training are directly proportional to the sequence length while inference needs only constant time per each step.
- General Context Handling: Mamba can easily manage sequences up to 1 million, which avoids the need for truncation.

The pre-trained Mamba models, such as mamba-130m, mamba-370m, and larger variants, are suitable for a wide range of applications. This research has opted for mamba-130m because it has low computational demands and great classification performance, making it apt for situations with limited resources. Figure 1 illustrates Mamba architecture.

F. EleutherAI/pythia-160m Tokenizer

The tokenization using EleutherAI/pythia-160m, one of the Pythia model suite by EleutherAI [8], is what the tokenizer actually does. Based on the GPT-NeoX tokenizer, it is used for inputting various Pythia models. The text is the tokenized version and is converted to numerical indices making it easier for other modules such as Mamba to use the data. It is the sequel of mamba-130m that boosts sequence modeling assignments, mostly long-text classification.

G. Mamba-130m Classifier

Our model is based on the mamba-130m architecture for classifying texts. Major components are:

- Embedding Layer: It is a 50280 x 768 matrix correspond to vocabulary size and embedding dimensions.

- Mamba Block Modules: Incorporating twenty-four sequential blocks that are linear transformations, convolutions, and activation functions.
- RMS Norm Layers: The layers that help normalizing which in turn provides stability during the training phase.
- Classification Head: A linear layer with input size 768 and output size nnn, where nnn denotes the number of classes.

One is trained on the classifier that can distinguish between 'real' and 'fake' articles. The classifier is thus provided with label datasets containing “real” and “fake” news. It starts with the cleaning of text (the removal of URLs, punctuation, etc.), exploratory analysis, and tokenization by tensorflow.keras.preprocessing.texttokenizer. The dataset is split into training (80%), validation (10%), and testing (10%) sets and converted to a format compatible with the Mamba architecture.

Hyperparameter Configuration: Key parameters include a learning rate 2e-05, batch size of 16, 3 epochs, and 500 warmup steps. Moreover, the model stops early if overfitting is detected.

Training and Evaluation: Trainer from the transformers library, which was used in the fine-tuning process, assesses the performance through accuracy, recall, precision, and F1-score [6]. These indicators have proven the model's great abilities in detecting fake news. Figure 2 illustrates our methodology.

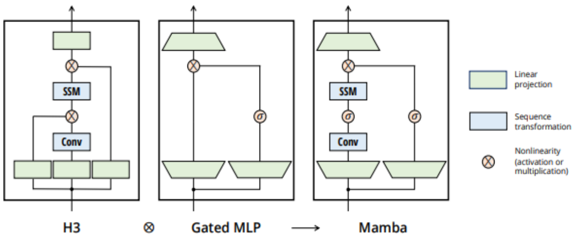

Figure 1 Mamba Architecture [10]

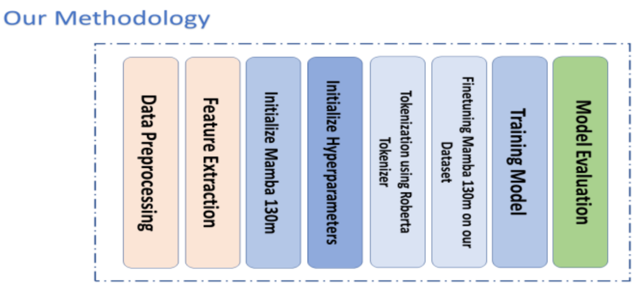

Figure 2 Our Methodology

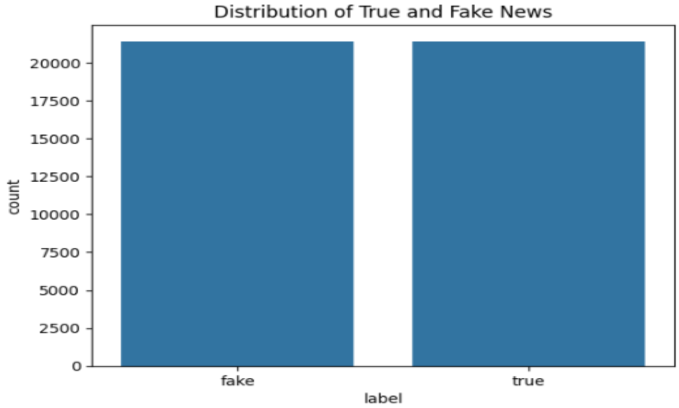

Figure 3 ISOT Dataset distribution

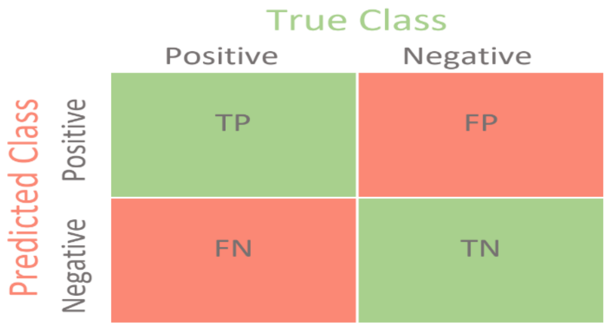

Figure 4 Confusion Matrix [31]

IV. DATASET AND EVALUATION METRICS

The ISOT dataset which is from Kaggle is considered as a standard in fake news detection research and it has been used in most of the studies. This data set includes headlines of English articles which are tagged as true or fake even though they don't contain full content. Our investigation verified that the dataset is balanced, with equal distribution of 50% real and 50% fake stories (FIGURE 3). This balance is favorable because it adjusted the skewness towards one side.

For the estimation of performance, this study will concentrate on binary classification metrics to see the quality and adequacy of the model. Reliable assessment is very important to be sure of strong performance of the unknown data as being impressed by accuracy that might give wrong assumptions especially with unbalanced data. A set of information-theoretic space measures including accuracy, precision, recall, and F1 score was utilized to compare the performance of different methods or scenarios.

Accuracy is how the prediction was successful but this is not a suitable method for unbalanced datasets. Precision refers to how well a model is able to detect actual class positives and decreases false positives, which is a major concern in domains like e-commerce recommendations. Whereas recall deals with recognizing all real positives which is an unavoidable thing in situations where false negatives are expensive. F-score/Detection Rate is a methodology that a given data set uses to compute a good evaluation what to do with True positives and false positives for example (training sets to be precise. in the case of imbalanced datasets [31].

The tool of this data, the confusion matrix (figure 4) plays the main role in the understanding of these metrics. The confusion matrix is a format that pursuits down true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) thus, a more detailed approach to classification errors. Anyway, more metrics were employed, our focus was on gaining insights into the model's robustness and reliability. Finally, the F1 score is reckoned to be best for performance evaluation of our classifier in this study.

V. RESULTS

In this section, firstly, we will describe the experimental setup used for training and evaluating the selected models on the three mentioned datasets. Then, we will discuss and evaluate our proposed Mamba-130m model on ISOT dataset.

H. Experimental Setup

The experimental setup used for training and evaluating the selected models on the datasets can be described as follows:

- Learning Rates: Each transformer model is trained using three predefined 2e-05 learning rate.
- Evaluation Metrics: The comparison between different approaches is established using micro f1-score and accuracy.
- Repeatability: To ensure reproducibility, we have utilized fixed seeds and maintained consistent batch sizes across the models and the datasets.
- Base Model Selection: Mamba-130m is chosen as the baseline model.
- Tokenizer Selection: We employed pythia-160m Tokenizer as the tokenizer.

I. Results discussion

The proposed Mamba-130m Classifier model was evaluated on ISOT dataset.

During the training process, the MambaTrainer technique was employed to enhance model performance on the training dataset. Validation set accuracy was monitored at various training stages to maintain a balance between accuracy and avoiding overfitting. Performance metrics were logged every 500 training steps.

The model demonstrated outstanding performance on the test set, achieving an overall accuracy of 99.83%. Precision, recall, and F1-score metrics were nearly perfect for both fake and real news, showcasing the model's exceptional ability to effectively distinguish between fake and real news.

The detailed evaluation results for the test dataset are in table 2.

TABLE 2 OUR MODEL RESULTSR

Accuracy	Precision	Recall	F1_score
99.8	99.8	99.8	**99.8**

The model proposed an outstanding test accuracy of 99.83%. The metrics involved in the classification reported nearly perfect precision, recall, and F1-Score for fake and real news alike, representing an additional accomplishment for the model in distinguishing between the two classes uniquely.

That being so, these results demonstrate the strong capability that the model has in detecting fake news with near-perfect accuracy. The assessment of the metrics shows that the model can really handle the challenges of distinguishing between fake and real news and hence its dependability in validation and testing environments. Such performance might affirm it as an implementable tool to fight misinformation.

When compared with other related studies, the proposed model is superiorly accurate and outperforms the current approaches for fake news detection. This is a clear demonstration of the goodness of fit and performance offered by the SSMs in the context of machine learning classification. Especially when contrasted with another research work done on the same dataset, its performance draws a mark as a model to measure against. In the table 3 below, a detailed comparison of methodologies and results is given.

TABLE 3 COMPARISON RESULTS WITH RELATED WORKR

Dataset	Methodology	Accuracy	Precision	Recall	F1_score
ISOT	Decision Tree	96.2%	96.3%	96.2%	96.2%
ISOT	Bert	-	-	-	99%
ISOT	Mamba (our Methodology)	99.8%	99.8%	99.8%	99.8%

We note that our methodology outperforms previous approaches on the same dataset and also in terms of speed in training and inference due to the simpler structure of the mamba model compared to transformers whose structure is more complex.

VI. CONCLUSION AND FUTURE WORK

The study is here presented with a primary novel proposal for fake news detection using the ISOT dataset, which achieves outstanding results with the proposed Mamba-130m Classifier model: 99.83% or near-perfect in accuracy, precision, recall, and F1-score versions, outperforming the pair-wise methodologies of decision trees and transformer-based approaches like BERT. Further, the simplicity of the structure facilitated quicker training and inference with excellent robustness and reliability.

These results indicate the model will provide a reliable and effective response to curbing injustice by providing its roadmap toward a solid groundwork for future studies. The techniques employed in the study are advanced and proven, thereby providing a general practical approach to one of the burning questions in information originality today.

Future extensions might include further validation and strengthening of these results:

- Testing on Diverse Datasets: Evaluating the model on datasets from a variety of sources guarantees generalization and lessens the potential biases.
- Increasing Dataset and Training Size: Bigger and more heterogeneous datasets will expand the model's ability to recognize heterogenous patterns and will boost performance.
- Hyperparameter Optimization: Different techniques like grid or random search can be used for optimizing learning rate and batch size of parameters to further enhance the performance of the model.

These improvements will strengthen the model's reliability and scalability and confirm its robustness for larger applications.

REFERENCES

[1] [1] A. Kim, P. L. Moravec, and A. R. Dennis, "Combating Fake News on Social Media with Source Ratings: The Effects of User and Expert Reputation Ratings," Journal of Management Information Systems, vol. 36, no. 3, pp. 931–968, Jul. 2019, doi: 10.1080/07421222.2019.1628921.

[2] [2] J. F. George, M. Gupta, G. Giordano, A. M. Mills, V. M. Tennant, and C. C. Lewis, "THE EFFECTS OF COMMUNICATION MEDIA AND CULTURE ON DECEPTION DETECTION ACCURACY Appendix A Creating the Stimulus Sets," 2018.

[3] [3] N. Kumar, D. Venugopal, L. Qiu, and S. Kumar, "Detecting Review Manipulation on Online Platforms with Hierarchical Supervised Learning," Journal of Management Information Systems, vol. 35, no. 1, pp. 350–380, Jan. 2018, doi: 10.1080/07421222.2018.1440758.

[4] [4] R. Chen and S. K. Sharma, "Learning and self-disclosure behavior on social networking sites: The case of Facebook users," European Journal of Information Systems, vol. 24, no. 1, pp. 93–106, Jan. 2015, doi: 10.1057/ejis.2013.31.

[5] [5] L. W. Lundmark, C. Oh, and J. C. Verhaal, "A little Birdie told me: Social media, organizational legitimacy, and underpricing in initial public offerings," Information Systems Frontiers, vol. 19, no. 6, pp. 1407–1422, Dec. 2017, doi: 10.1007/s10796-016-9654-x.

[6] [6] E. C. Tandoc, J. Jenkins, and S. Craft, "FAKE NEWS AS A CRITICAL INCIDENT IN JOURNALISM."

[7] [7] F. Olan, U. Jayawickrama, E. O. Arakpogun, J. Suklan, and S. Liu, "Fake news on Social Media: the Impact on Society," Information Systems Frontiers, 2022, doi: 10.1007/s10796-022-10242-z.

[8] [8] Y. Liu et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," Jul. 2019, [Online]. Available: http://arxiv.org/abs/1907.11692

[9] [9] P. Lu, S. Wang, M. Rezagholizadeh, B. Liu, and I. Kobyzev, "Efficient Classification of Long Documents via State-Space Models."

[10] [10] A. Gu and T. Dao, "Mamba: Linear-Time Sequence Modeling with Selective State Spaces." [Online]. Available: https://github.com/state-spaces/mamba.

[11] [11] K. Shahzad, S. A. Khan, S. Ahmad, and A. Iqbal, "A Scoping Review of the Relationship of Big Data Analytics with Context-Based Fake News Detection on Digital Media in Data Age," Nov. 01, 2022, MDPI. doi: 10.3390/su142114365.

[12] [12] K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, "Fake News Detection on Social Media: A Data Mining Perspective." [Online]. Available: http://www.journalism.org/2016/05/26/news-use-across-

[13] [13] L. Wan, G. Papageorgiou, M. Seddon, and M. Bernardoni, "Long-length Legal Document Classification," Dec. 2019, [Online]. Available: http://arxiv.org/abs/1912.06905

[14] [14] M. Ding, C. Zhou, H. Yang, and J. Tang, "CogLTX: Applying BERT to Long Texts." [Online]. Available: https://github.com/Sleepychord/CogLTX.

[15] [15] T. Wolf et al., "Transformers: State-of-the-Art Natural Language Processing." [Online]. Available: https://github.com/huggingface/

[16] [16] A. Vaswani et al., "Attention Is All You Need."

[17] [17] A. Gu, K. Goel, and C. Re, "Efficiently Modeling Long Sequences with Structured State Spaces," in International Conference on Learning Representations, 2022. [Online]. Available: https://openreview.net/forum?id=uYLFoz1vlAC

[18] [18] T. Wolf et al., "Transformers: State-of-the-Art Natural Language Processing." [Online]. Available: https://github.com/huggingface/

[19] [19] A. Katharopoulos, A. Vyas, N. Pappas, and F. Fleuret, "Transformers are RNNs: Fast Autoregressive Transformers with Linear Attention," 2020.

[20] [20] K. L. Tan, C. P. Lee, K. S. M. Anbananthen, and K. M. Lim, "RoBERTa-LSTM: A Hybrid Model for Sentiment Analysis With Transformer and Recurrent Neural Network," IEEE Access, vol. 10, pp. 21517–21525, 2022, doi: 10.1109/ACCESS.2022.3152828.

[21] [21] A. J. Keya, M. A. H. Wadud, M. F. Mridha, M. Alatiyyah, and M. A. Hamid, "AugFake-BERT: Handling Imbalance through Augmentation of Fake News Using BERT to Enhance the Performance of Fake News Classification," Applied Sciences (Switzerland), vol. 12, no. 17, Sep. 2022, doi: 10.3390/app12178398.

[22] [22] N. Seddari, A. Derhab, M. Belaoued, W. Halboob, J. Al-Muhtadi, and A. Bouras, "A Hybrid Linguistic and Knowledge-Based Analysis Approach for Fake News Detection on Social Media," IEEE Access, vol. 10, pp. 62097–62109, 2022, doi: 10.1109/ACCESS.2022.3181184.

[23] [23] M. K. Jain, D. Gopalani, and Y. K. Meena, "ConFake: fake news identification using content based features," Multimed Tools Appl, vol. 83, no. 3, pp. 8729–8755, 2024.

[24] [24] K. Nakamura, S. Levy, and W. Y. Wang, “r/Fakeddit: A New Multimodal Benchmark Dataset for Fine-grained Fake News Detection,” Nov. 2019, [Online]. Available: http://arxiv.org/abs/1911.03854

[25] [25] M. Ianni, E. Masciari, and G. Sperlí, “A survey of Big Data dimensions vs Social Networks analysis,” J Intell Inf Syst, vol. 57, no. 1, pp. 73–100, Aug. 2021, doi: 10.1007/s10844-020-00629-2.

[26] [26] L. Allein, M.-F. Moens, and D. Perrotta, “Preventing profiling for ethical fake news detection,” Inf Process Manag, vol. 60, no. 2, p. 103206, 2023.

[27] [27] E. Amer, K. S. Kwak, and S. El-Sappagh, “Context-Based Fake News Detection Model Relying on Deep Learning Models,” Electronics (Switzerland), vol. 11, no. 8, Apr. 2022, doi: 10.3390/electronics11081255.

[28] [28] R. K. Kaliyar, A. Goswami, and P. Narang, “DeepFakE: improving fake news detection using tensor decomposition-based deep neural network,” J Supercomput, vol. 77, no. 2, pp. 1015–1037, 2021.

[29] [29] H. H. Park, Y. Vyas, and K. Shah, “Efficient Classification of Long Documents Using Transformers,” Mar. 2022, [Online]. Available: http://arxiv.org/abs/2203.11258

[30] [30] D. Y. Fu, T. Dao, K. K. Saab, A. W. Thomas, A. Rudra, and C. Ré, “Hungry Hippos: Towards Language Modeling with State Space Models,” Dec. 2022, [Online]. Available: http://arxiv.org/abs/2212.14052

[31] [31] M. Vakili, M. Ghamsari, and M. Rezaei, “Performance Analysis and Comparison of Machine and Deep Learning Algorithms for IoT Data Classification.”