



A Hybrid BiLAT–SVM Framework with Uncertainty-Aware Decision Mechanism for Fake News Detection

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Abstract

The rapid dissemination of misinformation on social media needs the creation of precise and efficient detection systems to maintain information integrity and public trust. This study introduces the Uncertainty- and Confidence-Adaptive BiLAT-SVM (UCA-BiLAT-SVM) model, which integrates deep learning and machine learning techniques for the classification of fake news. The system uses Support Vector Machine (SVM) for categorising the obtained latent space and employs Bidirectional Long Short-Term Memory with Attention (BiLAT) for acquiring contextual and semantic representations of words. An entropy-based uncertainty mechanism is used to adaptively select or combine predictions when cases are ambiguous, to increase the reliability of the predictions. The use of the Bayesian Optimization with Hyperband (BOHB) algorithm for hyperparameter optimization. The proposed model is tested on Fake & Real News, FakeNewsNet and ISOT datasets with the commonly used performance metrics. Experimental findings show good performance results with accuracy up to 99.5% and F1 score up to 99.4%. The results show the effectiveness and scalability of the proposed approach for fake news identification that combines contextual representation learning, margin-based classification and uncertainty-aware decision-making.

Keywords: Fake News Detection, BiLAT, Support Vector Machine, Uncertainty-Aware Classification, BOHB Optimization.

1. Introduction

Social media platforms are expanding fast, and the transmission of information has intensified; yet, they have also become a channel for the propagation of disinformation. It poses considerable problems to public trust, decision-making, and the dependability of information. Thus, the automated identification of false information is a significant research problem in the domain of natural language processing. Conventional Machine Learning (ML) approaches rely on hand-crafted features that often fail to encapsulate intricate language and contextual patterns. Compared to this, Deep Learning (DL) models offer better contextual comprehension, but can be over fitted and less reliable in situations of uncertainty and ambiguity. The limitations indicate a need for a more comprehensive and dynamic detection system. [1]

There are recent studies that investigate hybrid methods combining ML and DL methods, taking advantage of their complementary advantages. For textual information, deep learning models like Bidirectional LSTM with Attention (BiLAT) are highly effective in modelling the contextual dependency and semantic relationships among sentences, and ML classifiers provide highly effective margin-based decision boundaries. But, most current hybrid techniques use fixed combination strategies, which do not consider the change in prediction confidence from sample to sample. This constraint results in poor performance, especially in situations of inconsistency and uncertainty, as in cases at the margins or when the predictions from any single model are unreliable. [2]

To overcome these issues, this paper introduces an Uncertainty- and Confidence-Adaptive BiLAT-SVM (UCA-BiLAT-SVM) framework based on deep contextual representation learning and margin-based classification, which adopts a dynamic decision mechanism. The proposed approach is based on learning discriminative latent representations using a BiLAT model followed by an SVM in the learned representation space to improve the boundaries for the classification. The uncertainty estimation mechanism adopted uses entropy to select and/or combine predictions from both models to achieve reliable performance at different confidence levels. Additionally, Bayesian Optimisation with Hyperband (BOHB) effectively optimises hyperparameters to improve the model's overall performance and scalability.

II. Literature Review

In the realm of false news detection research, advanced DL and hybrid architectures have replaced traditional ML techniques. The performance of the ML models SVM, LR, and RF has been tested and compared with the DL models CNN and LSTM by Alshuwaier & Alsulaiman (2025) [3], Tian et al. (2025) [4], and Mouratidis et al. (2025) [5]. Although DL models performed better in contextual understanding, most investigations were still comparative and did not provide integrated frameworks. In order to address these issues, Jaybhave et al. (2023) [8] showed the effectiveness of LSTM-based architectures, Al-alshaqi et al. (2024) [7] used the BERT model with ensemble learning, and Ayyasamy et al. (2025) [6] developed a hybrid LSTM-CGPNN model with metaheuristic optimisation. These techniques often offer great accuracy but are more difficult to calculate and train.

Strong advancements in multimodal and interaction-based learning have been prioritised recently. Hamed et al. (2023) [10] merged sentiment and emotion analysis to increase the detection rate, whereas Abdullah et al. (2026) [9] developed a multimodal ensemble model based on both textual and visual features. Qusef et al. [11] spoke about applying ML and DL techniques to identify bogus news in Arabic. Although these methods provide great accuracy, they are constrained by computing cost, noise in user-generated data, and a lack of cross-domain generalisation. These drawbacks highlight how crucial it is to have effective, scalable, and flexible false news detection systems.

III. Methodology

The proposed fake news detection framework UCA-BiLAT-SVM is presented in this section. The method is a well-structured pipeline based on deep contextual representation learning and margin-based classification. The framework is composed of pre-processing and embedding, representation learning with BiLAT, SVM-based latent space classification and adaptive decision making with uncertainty. Furthermore, Bayesian Optimization with Hyperband (BOHB) is used for the effective tuning of hyperparameters.

A. Dataset Description

To evaluate the proposed approach across diverse data distributions and authentic fake news contexts, three benchmarks were employed: Fake & Real News, FakeNewsNet, and ISOT.

TABLE I. COMPARATIVE ANALYSIS OF DATASETS USED FOR FAKE NEWS DETECTION

Dataset	Type	Data Source	Size	Strength
Fake & Real News Dataset [12]	Text-only	News articles (various sources)	44,919 articles	Balanced and clean for NLP tasks
FakeNewsNet [13]	Multi-modal (Text + Social)	News + Twitter interactions	24,000 + instances	Captures real-world propagation behaviour
ISOT Fake News Dataset [14]	Text-only	Reuters + unreliable sources	25,200 articles	High-quality labelled and diverse content

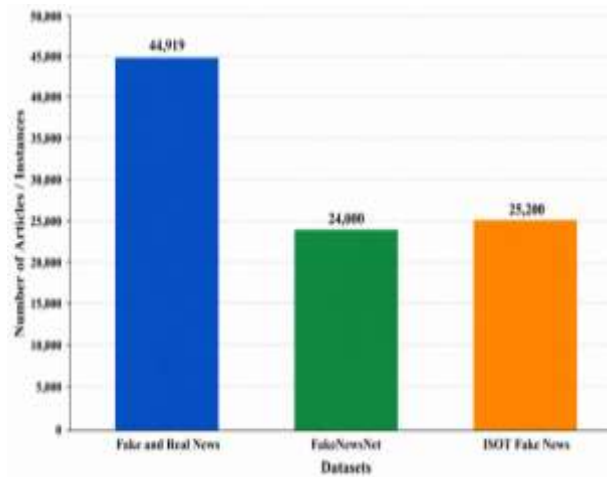


Fig.1 Evaluating Fake News Detection Datasets

In the figure, false news detection datasets are distributed. Particular datasets provide a wide range of news and social media information to allow for an effective assessment of fake news classification models for different types of misinformation situations.

B. Text Preprocessing and Embedding

Data preprocessing is essential for preparing chest X-ray images for model training, ensuring they are consistent and contain the desired information. All images are first scaled to a fixed resolution by applying $I_{resized} = Resize(I, H, W)$, and since X-rays are grayscale, they are either kept single-channel or expanded to three channels for compatibility with pre-trained models: $I_{3ch}(x, y, c) = I(x, y)$, $c \in \{1, 2, 3\}$. Next, pixel intensities are normalized to stabilize learning: $I_{norm} = I - I_{min} / I_{max} - I_{min}$, followed by contrast enhancement using histogram equalization: $I_{enhanced}(x, y) = (L - 1) \sum_{i=0}^{I(x,y)} p(i)$, where L is the number of intensity levels. Noise is reduced through Gaussian filtering: $I_{denoised}(x, y) = \sum_{i=-k}^k \sum_{j=-k}^k I(x - i, y - j) \cdot G(i, j)$ and data augmentation like rotation is applied to improve generalization. To address class imbalance, weights are assigned as $w_i = N/k \cdot n_i$, ensuring balanced learning across classes. One-hot encoding converts category labels to numbers: $y_i = \{1 \text{ if class} = i, 0 \text{ otherwise}\}$, enabling effective multi-class classification.

C. Hyperparameter Optimization using BOHB

Hyperparameter optimisation improves model efficiency and generalisation. This study uses Bayesian Optimisation with Hyperband (BOHB) to effectively explore a hyperparameter space with limited computing resources. Let Θ be a set of configurations in the search space and let $\theta \in \Theta$ be a particular configuration from the search space Θ . The aim is to find the best configuration: $\theta^* = \arg \max_{\theta \in \Theta} F(\theta)$, with the validation performance metric $F(\theta)$.

Direct evaluation of $F(\theta)$ is hard and time consuming, which is why BOHB uses a probabilistic model as a surrogate: $F(\theta) \sim GP(\mu(\theta), \sigma^2(\theta))$, where the mean performance $\mu(\theta)$ and uncertainty (variance) $\sigma^2(\theta)$ denotes uncertainty (variance). The next configuration is selected by maximizing an acquisition function: $\theta_{t+1} = \arg \max_{\theta} \alpha(\theta)$. One popular option is to use Expected Improvement: $\alpha_{EI}(\theta) = E[\max(0, F(\theta) - F(\theta^+))]$, where θ^+ is the best observed configuration. BOHB includes Hyperband to efficiently distribute computational resources. Each configuration is tested on a specific budget b , which is defined as a number of training epochs, and is tested on the following: $b \in \{b_{min}, \eta b_{min}, \eta^2 b_{min}, \dots, b_{max}\}$, where, b_{min} is minimum budget, b_{max} is maximum budget and $\eta > 1$ is reduction factor. The number of configurations at each stage is: $n_i = \lceil n_0 / \eta^i \rceil$, here n_0 is the initial number of configurations. Each stage, configurations are ordered by performance: $F(\theta_1) \geq F(\theta_2) \geq \dots \geq F(\theta_n)$. Only the top fraction $1/\eta$ is retained: $\theta_{i+1} = Top_{1/\eta}(\theta_i)$ while the remaining configurations are discarded. A validation metric is used for each configuration. The selected optimal configuration is: $\theta^* = \arg \max_{\theta \in \Theta_{evaluated}} F(\theta)$. The completed model is then trained using θ^* on the whole training dataset.

Table II. Hyperparameter Sets for UCA-BiLAT-SVM Framework

Model	Hyperparameters	Set 1	Set 2	Set 3
BiLAT	Embedding Dimension	64	128	256
	BiLSTM Hidden Units	32	64	128

	Number of BiLSTM Layers	1	2	3
	Dropout Rate	0.2	0.3	0.5
	Activation Function	ReLU	LeakyReLU	ELU
	Learning Rate	0.001	0.0005	0.0001
	Batch Size	16	32	64
	Number of Epochs	30	50	70
SVM	Kernel Function	Linear	RBF	Polynomial
	Regularization Parameter (C)	0.1	1.0	10
	Gamma	0.01	0.001	auto
BOHB	Minimum Budget (Epochs)	10	20	30
	Maximum Budget (Epochs)	30	50	70
	Reduction Factor (η)	2	3	4

The above shows the hyperparameter search space explored with BOHB to optimize the proposed UCA-BiLAT-SVM framework.

D. Classification

The classification stage is designed to correctly classify fake & real news articles using both deep learning and machine learning approaches. Individual performances of baseline models such as SVM [15], LSTM [16] and BiLAT are assessed to evaluate their baseline performance. SVM generates good decision boundaries based on the margin, whereas BiLAT is able to capture the contextual dependency in text. Single-model forecasts are however, not always reliable in situations of uncertainty. To overcome this, the proposed UCA-BiLAT-SVM framework is designed to combine deep representation learning with margin-based classification via uncertainty-aware adaptive mechanism.

Proposed: Uncertainty and Confidence-Adaptive BiLAT-SVM (UCA-BiLAT-SVM)

The proposed system integrates deep contextual learning, which leverages state-of-the-art representation learning techniques, and a margin-based decision modelling technique to ensure robust and reliable classification. The input sequence $x = \{w_1, w_2, \dots, w_n\}$ is first transformed into an embedding space: $X = \{v_1, v_2, \dots, v_n\}$, $v_i \in R^d$. The backbone of the BiLSTM Attention Transformer (BiLAT) is a Bidirectional LSTM network processing the embedded sequence: $\vec{h}_t = LSTM_f(v_t, \vec{h}_{t-1})$, $\overleftarrow{h}_t = LSTM_b(v_t, \overleftarrow{h}_{t+1})$, $h_t = [\vec{h}_t; \overleftarrow{h}_t]$. An attention mechanism is used to attend to the relative importance of each token:

$$e_t = \tanh(W_a h_t + b_a), \quad \alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^n \exp(e_i)}$$

BiLAT introduces an attention refinement process $\tilde{\alpha}_t = F(\alpha_t, h_t)$ to boost discriminative performance, where $F(\cdot)$ is a nonlinear function for tuning attention weights according to the contextual interactions. The refined context representation is calculated as: $c = \sum_{t=1}^n \tilde{\alpha}_t h_t$. The deep model gives a probabilistic prediction: $p_{DL} = \sigma(W_c c + b_c)$ and the BiLAT model has rich contextual dependencies, however, neural predictions might be unreliable near decision boundaries. To solve this problem, the learned representation c is then sent to a Support Vector Machine (SVM) that builds a function to maximize the margin, denoted as: $f_{SVM}(c) = w^T c + b$. The SVM output is transformed into a probability score:

$$p_{SVM} = \frac{1}{1 + \exp(-f_{SVM}(c))}$$

To integrate both models in a more efficient manner, an uncertainty-aware decision mechanism is added. The entropy is used to quantify the confidence of the deep model: $H(p_{DL}) = -[p_{DL} \log(p_{DL}) + (1 - p_{DL}) \log(1 - p_{DL})]$. The final prediction is made by implementing a confidence adaptive strategy:

$$f(x) = \begin{cases} p_{DL} & , \quad \text{if } H(p_{DL}) < \tau_1 \\ p_{SVM} & , \quad \text{if } H(p_{DL}) > \tau_2 \\ \alpha p_{DL} + (1 - \alpha) p_{SVM}, & \text{otherwise} \end{cases}$$

The output of the final classification is: $\hat{y} = \{1, p_{final} \geq 0.5 ; 0, \text{otherwise}\}$. This blend of techniques results in better generalization and stability—deep contextual learning for confident prediction, margin-based classification for robustness in ambiguous areas.

Input: Training dataset D , Validation dataset D_{val} , Hyperparameter space θ , Maximum Computational budget B

Output: θ^* , $\hat{y}$

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Initialize BOHB with  $\Theta$ , best score  $F_{best} \leftarrow \mathbf{0}$ , best configuration  $\theta^* \leftarrow \emptyset$ 
while budget B not exhausted do
    Sample configuration  $\theta \in \Theta$  using BOHB

    Train BiLAT using  $\theta_{DL}$  for b epochs on  $D_{train}$ 
    for each sample x in  $D_{train}$  and  $D_{val}$  do
        Compute embedding X
        Compute hidden states  $h_t$  using BiLSTM
        Compute attention weights  $\alpha_t$ 
        Apply refinement  $\rightarrow \tilde{\alpha}_t$ 
        Compute context vector c
        Compute deep probability  $p_{DL}$ 
    end for

    Train SVM using  $\theta_{SVM}$  on representations c (from  $D_{train}$ )
    for each sample x in  $D_{val}$  do
        Compute  $p_{DL}$  from BiLAT
        Compute  $p_{SVM}$  from SVM
         $H \leftarrow -[p_{DL} \log(p_{DL}) + (1 - p_{DL}) \log(1 - p_{DL})]$ 
        if  $H < \tau_1$  then
             $p_{final} \leftarrow p_{DL}$ 
        else if  $H > \tau_2$  then  $p_{final} \leftarrow p_{SVM}$ 
        else  $p_{final} \leftarrow \alpha \cdot p_{DL} + (1 - \alpha) \cdot p_{SVM}$ 
        end if
        Predict label  $\hat{y}$  using  $p_{final}$ 
    end for
    Evaluate  $F(\theta)$  using F1-score on  $D_{val}$ 
    Update BOHB model with  $(\theta, F(\theta))$ 
    if  $F(\theta) > F_{best}$  then
         $F_{best} \leftarrow F(\theta)$ 
         $\theta^* \leftarrow \theta$ 
    end if
end while
Return  $\theta^*$  and final trained model

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The model then cleans and encodes the text into numerical vectors, after which the BiLAT network analyzes these vectors to comprehend context and make an initial prediction. Meanwhile, the internal representation acquired by BiLAT is fed to an SVM to build a robust decision boundary for classification. In the absence of blind faith, the system evaluates the confidence of the BiLAT prediction by using entropy, and if it is confident, it takes the BiLAT prediction, if not, it takes the SVM decision, if neither, it combines both predictions. While doing so, BOHB optimizes the settings of all models, testing their performance efficiently and retaining only the best ones. This leaves a more accurate and more reliable system, particularly during challenging or unclear situations.

IV. Result And Discussion

This section provides a thorough assessment of the proposed UCA-BiLAT-SVM model on three benchmark datasets. The performance is evaluated based on standard performance metrics [16] to get a balanced measure of classification performance. To optimize the training configuration for different computational budgets, BOHB was used to identify the optimal training configuration for different computational budgets.

Table IV. Performance Comparison Using BOHB Optimization on Fake & Real News Dataset

Model	Accuracy (%)	Precision	Recall	F1-Score
UCA-BiLAT-KNN	98.6	98.4	98.7	98.5
UCA-BiLAT-LR	98.8	98.6	98.9	98.7
UCA-BiLAT-RF	99.0	98.9	99.1	99.0
UCA-BiLAT-SVM	99.3	99.1	99.4	99.2

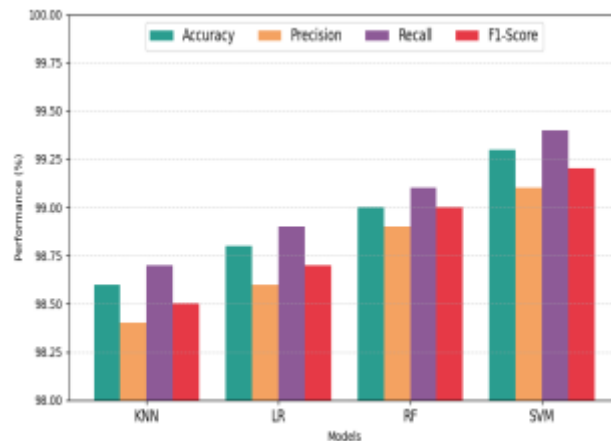


Fig.2 Performance Comparison of models on Fake & Real News Dataset

The Fake & Real News dataset performance comparison suggests BiLAT with various classifiers works. The recommended UCA-BiLAT-SVM model has 99.3% accuracy and 99.2% F1 score, outperforming KNN, LR, and RF. In the taught latent space, SVM performs best in classification and delivers the best decision bounds.

Table V. Performance Comparison Using BOHB Optimization on FakeNewsNet Dataset

Model	Accuracy (%)	Precision	Recall	F1-Score
UCA-BiLAT-KNN	98.9	98.7	99.0	98.8
UCA-BiLAT-LR	99.1	98.9	99.3	99.0
UCA-BiLAT-RF	99.3	99.1	99.4	99.2
UCA-BiLAT-SVM (Proposed)	99.5	99.3	99.6	99.4

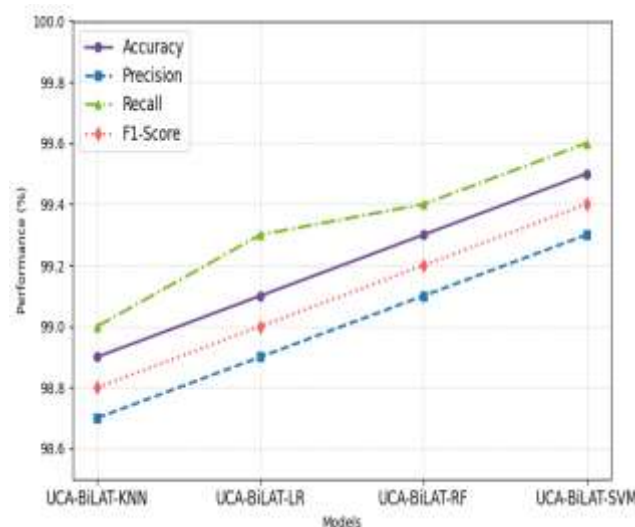


Fig.3 Model Performance Comparison of models on FakeNewsNet Dataset

All hybrid models performed well with more than 98.9% accuracy on FakeNewsNet. The proposed UCA-BiLAT- The SVM attained an accuracy of 99.5% and an F1 score of 99.4% on the suggested dataset, so confirming the efficacy of the proposed technique.

Table VI. BOHB Optimization on ISOT Fake News Dataset Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score
UCA-BiLAT-KNN	98.8	98.6	99.0	98.8

UCA-BiLAT-LR	99.0	98.8	99.2	99.0
UCA-BiLAT-RF	99.2	99.0	99.3	99.1
UCA-BiLAT-SVM (Proposed)	99.4	99.2	99.5	99.3

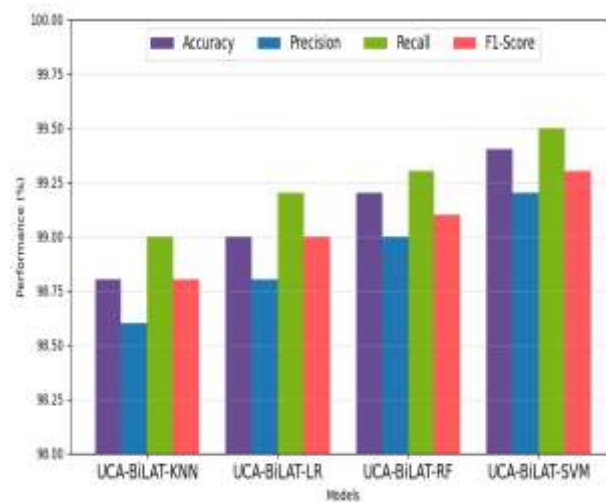


Fig.4 Performance Comparison of models on ISOT Dataset

All classifiers show comparable ISOT trends. UCA-BiLAT-SVM stood out with 99.4% accuracy and 99.3% F1 score, surpassing KNN, LR, and RF classifiers. The suggested framework is strong, resilient, and generalizable.

Table VII. BOHB Optimization Analysis across Different Datasets

Metric	Hyper parameter Set	Fake & Real News	FakeNewsNet	ISOT
Validation Loss	Set 1	0.126	0.118	0.121
	Set 2	0.079	0.071	0.075
	Set 3	0.041	0.036	0.039
Training Time (min)	Set 1	18	22	20
	Set 2	27	31	29
	Set 3	35	40	37
Accuracy (%)	Set 1	98.4	98.7	98.5
	Set 2	99.0	99.2	99.1
	Set 3	99.3	99.5	99.4
F1-Score	Set 1	98.3	98.6	98.4
	Set 2	98.9	99.1	99.0
	Set 3	99.2	99.4	99.3

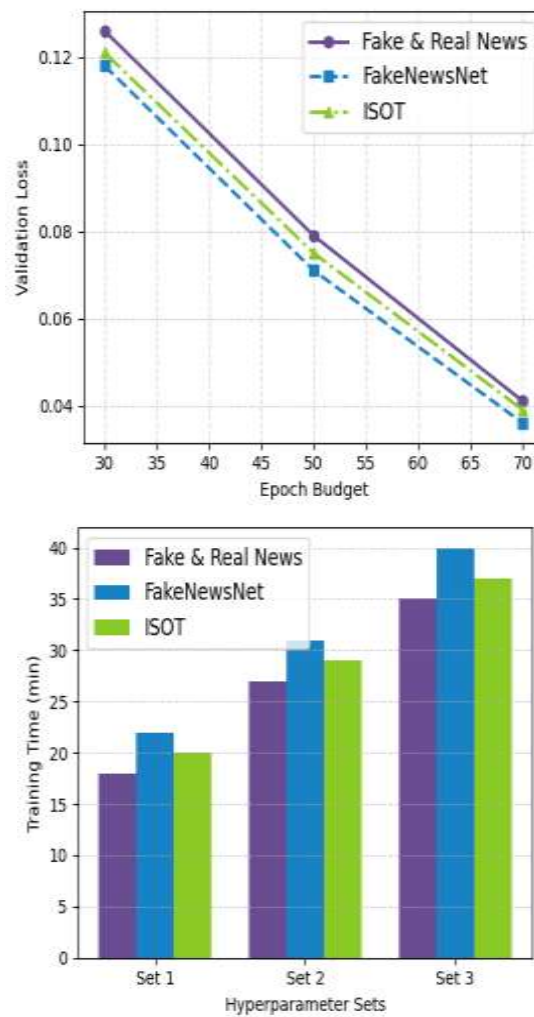


Fig.5 Validation Loss and Training Time Analysis under BOHB Optimization

The results of the BOHB optimization illustrates that increasing the amount of money spent on training the model gives rise to better performance on all datasets. The accuracy and F1-score values increase continuously from Set 1 to Set 3, while the validation loss decreases. The results for set 3 was best, indicating the effectiveness of BOHB in finding the best hyperparameter configuration.

Table VIII. Performance Analysis across Different Stages of the Proposed Pipeline

Pipeline Stage	Fake & Real News		FakeNewsNet		ISOT	
	Acc	F1	Acc	F1	Acc	F1
Raw Text (No Pre-processing)	88.6	88.2	87.9	87.5	89.2	88.9
Pre-processing Applied	91.8	91.5	91.2	90.9	92.4	92.0
+ Embedding Layer	94.6	94.2	94.1	93.7	95.0	94.6
+ BiLAT Representation Learning	98.3	98.0	99.0	98.9	98.6	98.5
+ Latent-Space Classification (SVM)	98.9	98.7	99.2	99.1	99.0	98.9
+ UCA-BiLAT-SVM (Proposed)	99.3	99.2	99.5	99.4	99.4	99.3

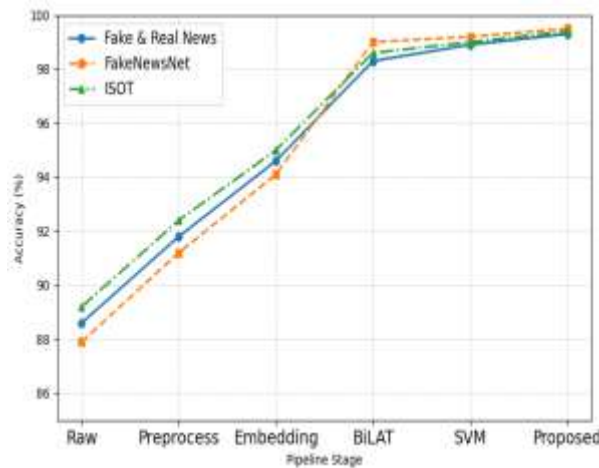


Fig.6 Step-wise Accuracy Improvement across Datasets

Each component of the proposed framework is emphasized in the step-wise analysis. The performance gradually increases in going from preprocessing and embedding to the representation learning, BiLAT, and SVM classification.

V. CONCLUSION

This research proposes the UCA-BiLAT-SVM system for false news detection using deep contextual representation learning and margin-based classification. The BiLAT model is able to learn semantic and contextual dependencies, and the SVM classifier improves the boundaries between the learned latent space classes. In uncertain situations, an entropy-based adaptive mechanism dynamically chooses or combines predictions for greater reliability. BOHB is used for efficient parameter optimization of hyperparameters. Experimental results on Fake & Real News, FakeNewsNet and ISOT datasets confirm the efficiency of the proposed framework with up to 99.5% of accuracy and 99.4% of F1-score. The findings demonstrate that the proposed approach with contextual learning, margin-based classification, and adaptive decision-making is a powerful and scalable approach to fake news detection.

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