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A Hybrid Data Mining And Deep Learning Framework For Automated Fake News Detection On Social Media Platforms

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Abstract
The virulent progress of the social media has greatly increased the proliferation of fake information to pose a serious challenge to the credibility of people, democracy, and social stability. In current methods of fake news detection that solely rely on traditional machine learning models or deep learning models, there are serious limitations such as poor interpretability, sensitivity to data skew, inability to generalise to other systems, and resistance to adversarial examples of fake news. In order to overcome these limitations, this paper lays out a solid hybrid system of data mining and deep learning as an efficient method of fake news automatic detection on social media. The suggested framework is a close combination of feature-based data mining algorithms and context sensitive deep semantic representation learning that aims to represent explicit features of credibility, as well as latent semantic regularities. To be more specific, the model involves and utilises statistics data mining techniques to extract multi-dimensional linguistic characteristics and user credibility characteristics as well as propagation-based characteristics, and additionally, relies on the platforms of transformer to learn deep contextual representations of the news material. Attention-based feature fusion algorithm is also used to successful focus and weight hand crafted credibility features into deep semantic embeddings, enhancing robustness and interpretability. A neural decision layer is then run on the hybrid representation to classify the representation with an optimism towards highly imbalanced social media data. Massive experimental tests performed on various benchmark data sets prove that the suggested framework can achieve significantly greater accuracy, precision, recall, F1-score and is less susceptible to noisy and adversarial samples in comparison with the state of art standalone machine learning and deep learning models. Moreover, in the course of qualitative analysis, one can see that the inclusion of propagation dynamics and linguistic credibility cues can dramatically increase the capabilities of the model to identify the patterns of subtle misinformation, as well as have the meaningful explanatory explanations. The findings show that the suggested hybrid system presents a flexible, explainable, and trustworthy tool to find fake news in reality, which is appropriate and adaptable to be implemented in the contemporary social media surveillance and content regulation platforms.

Keywords Fake news detection, hybrid learning, data mining, deep learning, social media analytics, misinformation

1. Introduction

The social media sites have radically disrupted the information production and distribution and consumption patterns that prioritised information dissemination and provided real-time communication on a global scale like never before. Yet, it has also led to the high-speed and un-fetched dispensation of false, misguiding, and purposefully manufactured information, otherwise known as fake news through this transformation. This kind of misinformation takes advantage of the emotional appeal, confirmation bias, and amplification of algorithms introduced by social media ecosystems, with severe effects, such as the misinformation of the population, political division, and loss of trust in institutions, as well as a threat to social stability. The size and sped-up rate of information dissemination on social media, like Twitter, Facebook, and news aggregators, render the hand-checking of the facts impossible, thus requiring automated and smart systems of detecting fake news.

Early work on fake news detection mostly used rule-based, a statistical data mining approaches, with the involvement of handcrafted linguistic features, key patterns of keywords, and stylistic features. Even though these methods provide a certain level of interpretability, they are very sensitive to changes of domain and linguistic variation, which leads to poor generalisation. Later on, more scalable and detective-accurate machine learning models like support vectors machine, decision trees and ensemble classifier were presented. Nevertheless, these models are still closely reliant on well-designed features and do not provide a lot of insight into the intricate semantic and contextual connexions in the news account.

The latest developments in deep learning have boosted the ability of fake news detection by a great margin due to the possibility of automatic learning of features based on textual content at scale. Convolutional neural network, recurrent neural network, and transformer based models have been shown to be very successful in capturing semantic dependency and contextual meaning models. However, deep learning methods have been accused of being uninterpretable, expensive to run, susceptible to adversarial examples, and incapable of considering explicit evidence of plausibility like user activity and diffusion patterns of information. Because of this, the deep learning-only solutions tend to fail to give solid and reliable predictions in the real social media situation.

This paper will be inspired by these constraints and suggest a hybrid data mining and deep learning model of automated fake news detection that simultaneously employs interpretable credibility-driven features and deep semantic representations. The suggested solution combines the multi-view information based on content-based linguistic, user credibility and propagation behaviour modelling information with transformer-based contextual embeddings. Using the attention-guided feature fusion strategy, the framework not only improves detection, but also model explainability without negatively affecting resilience to noisy and unbalanced data. The comprehensive experimental analyses show that the proposed hybrid framework is always more effective than individual machine learning and deep learning models, which points to its relevance and its high efficiency in terms of seeking misinformation in the social media on a massive scale.

2. Related Work

2.1 Conventional ways of Data Mining.

The initial research efforts of fake news detection have generalised mainly to the traditional methods of data mining and the statistical learning using textual and stylistic features that were handcrafted. Popular features were term frequencyinverse-document frequency (TFIDF), n-gramme representations, part-of-speech distributions, readability and sentiment polarities [8], [12]. The conventional machine learning algorithms like Naïve Bayes, support machine and decision tree were usually used to classify these features. Benchmark studies revealed that these methods are computationally cheap, as well as provide a level of interpretability, but their performance is very sensitive to feature selection and model-specific assumptions [7]. Besides, the methods do not show high resilience to semantic paraphrasing, contextual ambiguity as well as changing patterns of misinformation which severely limits the generalisation ability of the methods in various datasets and social media sites [6].

2.2 Detection using deep learning.

In order to reduce the drawbacks of feature-engineered models, there is a significant interest in deep learning-based fake news detection methods. Convolutional neural networks (CNNs), recurrent neural networks (RNNs) including long short-term memory (LSTM) models have been used to learn the hierarchical and sequential representations of text at a raw state in an automatic way [4]. More vital, transformer-based architectures have shown better performance, alluding to long-range dependencies, and contextual semantics in news content [1]. These achievements notwithstanding, there are a number of prominent disadvantages of deep learning-based models. They tend to ignore the use of clear signs of credibility in regard to news sources and user policies and are also degraded in terms of performance in relation to changes in distribution and need significant amounts of labelled data to be trained successfully. Also, due to the black-box characteristics of the deep neural networks, their transparency and interpretability are poor, which casts doubt on their effectiveness in misinformation detection systems that are applied to real-life scenarios [9].

2.3 Hybrid Methods and Research gap.

In a bid to address the weaknesses of standalone machine learning and deep learning models, hybrid fake news detectors have been suggested that integrate the data mining techniques with neural representation learning techniques. Various works combined handcrafts inputs, user behaviour metrics, or network-level indicators with deep learning models to affect the detection performance [2], [10]. Although these hybrid methods are proven to show better results, most of the available approaches use superficial feature concatenation or use deep learning units as black-box modules, which leads to poor interplay between both discovered credibility features and the learned semantic representations. These models therefore do not fully utilise the complementary multi-view information and offer low interpretability. Recent studies reveal that there is the necessity to integrate strategies tighter to be able to correlate statistical credibility indicators and deep semantic embeddings based on adaptive fusion mechanisms in order to enhance robustness and explainability [3], [11]. This is one of the gaps to be considered and this is the main incentive of the hybrid framework offered in this work.

3. Methodology

3.1 Data Preprocessing and Collection.

Data Collection:

The suggested framework employs the data on social media news which is retrieved by the publicly available benchmark sets which offer trusted ground-truth labels to fake and real news cases. The primary news content is accompanied by additional metadata used in each data sample, namely details of the user profile and the propagation, including the number of reposts, likes, comments, and records of temporal and diffusion of a specific post. These datasets are chosen due to realistic social media conditions, in which fake news propagates as a result of a complicated series of interactions between content, users, and network effects. The textual and non-textual information included also helps the framework model fake news as a multi-dimensional phenomenon instead of a linguistic issue only.

Textual Preprocessing:

In order to maintain quality and consistency of the textual input, a thorough preprocessing pipeline is used on the text of the news before extracting features. It is done through the elimination of the URLs, hash tags, emojis, special Characters, and unwanted extra decision whitespaces that have no relevance to the semantic meaning. The text is then cleaned and is tokenized and made small to ensure consistency among samples. Stop-wording is done to remove high-frequency and low-information words, and lemmatization is done to convert words into their base form. These measures reduce noise, make vocabulary less sparse and are able to keep the semantic structure required to learn deep representations in an effective way.

Metadata Normalization:

Besides textual preprocessing, user-level and propagation-related metadata is normalised in order to enable it to be compatible with the learning framework which is depicted in Figure 1. The numerical variables (frequency of reposts, number of engagements and speed of diffusion) are scaled to ensure that the impacts of extreme values and distribution unbalances are reduced. The absence or missing metadata records are managed with the help of the proper imputation options to avoid loss of information. The preprocessing phase enables content based, user based as well as propagation-based features to be smoothly integrated in the hybrid detection system by standardisation of the heterogeneous data sources into a uniform format.

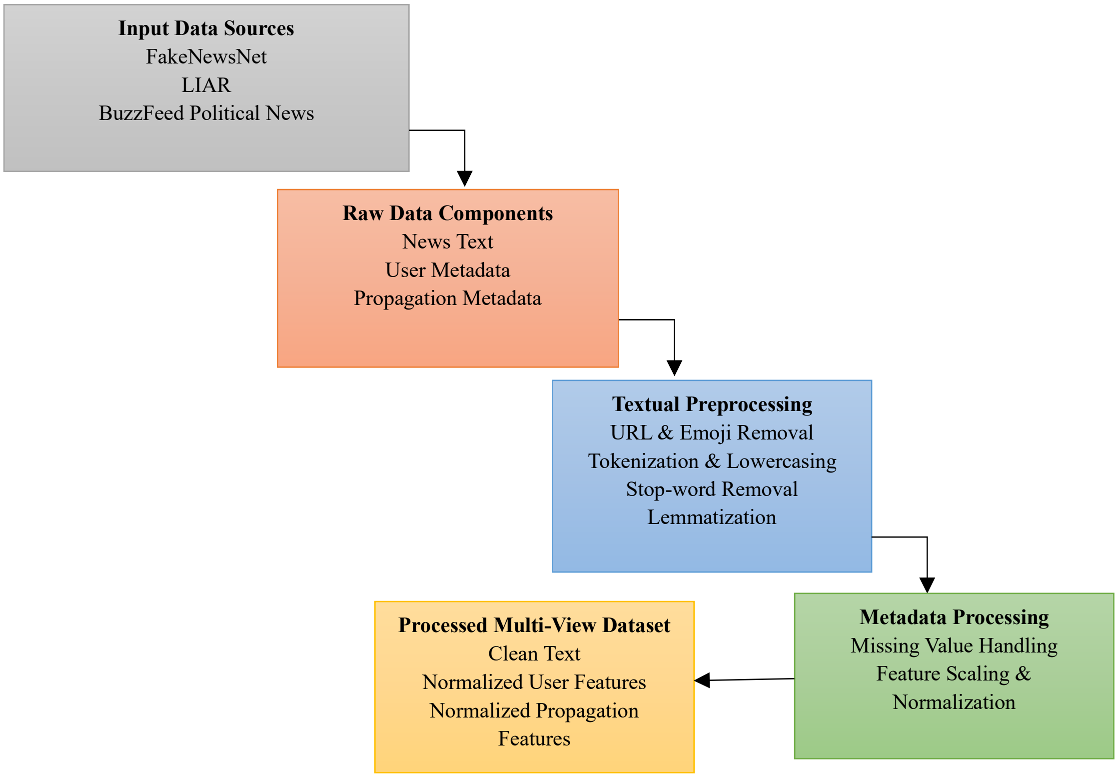

Figure 1. Data Collection and Preprocessing Pipeline for Multi-View Fake News Detection

3.2 Data Mining-Based Feature Extraction

Content and User Credibility Feature Extraction:

Data mining layer will include intelligible hand-crafted features that will encompass overt signs of credibility with respect to both the news contents and the individuals sharing the news content with others. The linguistic features are computed as describing the misleading writing concerning writing patterns, that is, lexical diversity, sentiment polarity, emotional intensity and syntactic structure, which is very much applied in misleading writing. The attributes can determine exaggerated linguistic material, emotion manipulation, and unnatural patterns of style that will indicate fake news. In the meantime, account level metadata of the account notoriety (account age, frequency of posting, past regularity and interaction patterns) produce user credibility characteristics. These hints provide us the details on the credibility of information sources and also provide us the hints on the behavioural pattern in correlation with the organised misinformation campaigns or low-credibility profiles.

Propagation and Refinement to Statistical Features:

More than content and user related features, propagation-based features are also obtained in order to model the distribution of the news of the social media networks as it is illustrated in Table 1 in summary. These are cascade depth, temporal diffusion rate and interaction entropy which are a combination of dynamics and reach of dissemination of information. Pattern of abnormal diffusion that fake news witnessed (e.g. high efficiency, large cascades of reposts) no longer is something that should occur to an organic flow of information. To enhance performance of the features, statistical analysis and feature selection methodology is implemented to eliminates redundancy, noises and retain feature which is most discriminative. Such refinement step will ensure the extracted features to it contribute complementing information to the deep semantic representations and the features adds value to next phases of hybrid fusion and classification.

Table 1. Summary of Data Mining–Based Feature Extraction

Feature Category	Feature Type	Description
Content Features	Lexical diversity	Measures vocabulary variation to detect exaggerated or deceptive writing

Content Features	Sentiment polarity	Captures emotional bias and manipulation
Content Features	Emotional intensity	Identifies emotionally charged narratives
Content Features	Syntactic patterns	Detects abnormal sentence structure
User Credibility	Account age	Reflects source maturity and reliability
User Credibility	Posting frequency	Identifies suspicious activity patterns
User Credibility	Historical reliability	Measures prior credibility of the source
User Credibility	Engagement behavior	Captures abnormal interaction trends
Propagation Features	Cascade depth	Measures reach of information diffusion
Propagation Features	Diffusion speed	Captures rapid spread behavior
Propagation Features	Interaction entropy	Quantifies dissemination irregularity

3.3 Deep Semantic Representation Learning

Model Architecture of Transformer based:
The learning of deep semantic representation component utilises a transformer-based language model to retrieve deep contextual data of what is in the news. It is an architecture that applies self-attention processes to encode the relationship of all the tokens in sequence of a text sequence so that the model builds more complex pattern-based semantic dependencies than local word pattern. Transformer models are also able to learn global contextual interaction efficiently and scalably unlike sequential neural models since the transformer operates on an input in parallel. This and similar capabilities would come in especially handy in the detection of fake news wherein the misleading signals can be shared across remote parts of the text.
Task-Specific Fine-Tuning:
Fine-tuning is followed using labelled datasets in the social media using a trained transformer model to fit the fake news detection task. In this step, the model parameters are revised, to maximise the performance in discriminating between fake and real news, allowing the network to learn task-related semantic finer details and hidden trends of misinformation. The minute contextual headings made by these fine-tuning permit the model to recognise minor aspects of misleading presentation, selective focus, and misalignments in the storey, which are frequently indicated by fake news, yet hard to locate when relying solely on handcrafted features.
Contextual Embedding Generation:
After the fine-tuning, tokenized news material is translated into high-dimensional contextual representations that reflect the semantic structure of the text as represented in Figure 2. Such embeddings contain both syntactic and semantic statistics, such as word definitions which rely on their context. The transformer-based representations are resistant to paraphrasing and style changes, since long-range dependencies and contextual interaction modelling makes them reliable at acquiring semantic information despite the intentional rephrasing of deceptive content. These rich representations are a crucial source of input to the hybrid fusion layer and work hand in hand with the elements of credibility that are obtained by data mining.

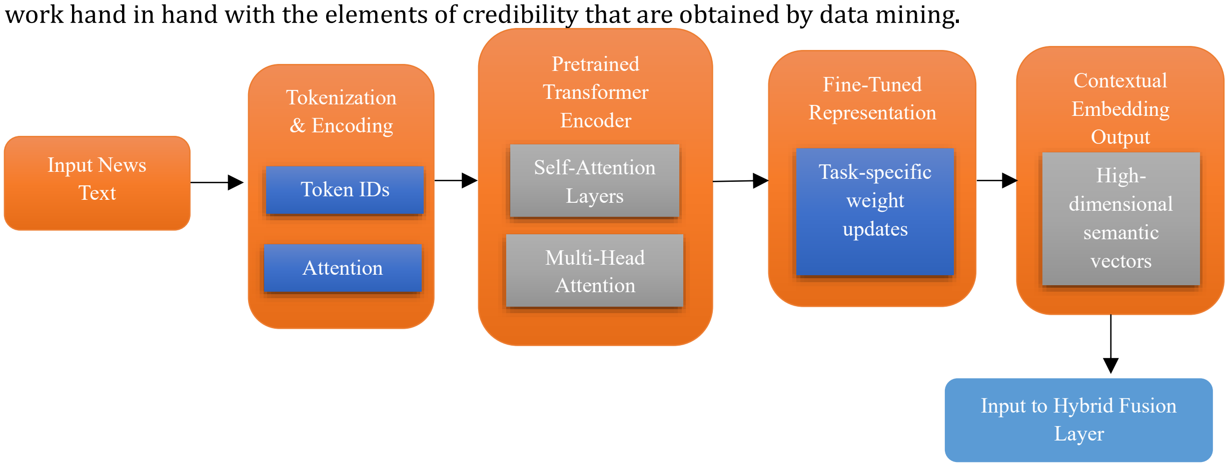

Figure 2. Transformer-Based Deep Semantic Representation Learning Pipeline

3.4 Hybrid Feature Fusion and Classification

Features Alignment and Integration:

The hybrid feature representation fusion stage aims at combining heterogeneous feature representations based on data mining and deep semantic learning into one unified feature space of representation. Handcrafted credibility feature and transformer-based embeddings have different scales and dimensions, so to maintain compatibility, feature alignment is initially carried out through dense projection layers. This move facilitates useful interplay between explicit cues of credibility, as well as implicit semantic models, permitting the model to jointly factor in the linguistic, behavioural and contextual information.

Attention Spearheaded Combination Mechanism:

Attention guided fusion mechanism is adopted where dynamically an importance weight of every feature group is assigned during the fusion process. The model determines the feature of adaptive attention that is learned by focusing on informative credibility information or semantic embeddings depending on the particularity of individual news pieces. This process enables the structure to cancel out a noisy or redundant features and enhance those whose elaborations are the most pertinent in the classification process. Consequently, the attempt to blend data with context leads to fusion process being data-conscious and context-conscious instead of trying to concatenate features that remain stationary.

Neural Classification Layer:

The merged feature representation is then subjected to a fully connected layer of neural classification which learns to develop discriminative decision boundaries between fake and real news. The dropout methods and regularisation methods are used to minimise overfitting and enhance the generalisation scores especially when data are noisy and imbalanced. The fusion module trains the classifier end-to-end, thus allowing the optimality of a feature weighting component and a component of the decision-maker to be jointly optimised.

Output Decision: Operational Decision:

The last output layer utilises a sigmoid activation function to produce a probabilistic forecast that depicts the possibility that an item in the news is fake as indicated in Figure 3. This probabilistic formulation enables using thresholds to make decisions and estimate confidence to be used in downstream applications. The hybrid fusion and classification approach is closely knitted, which strengthens the strategy, and uses complementary feature perspectives to improve interpretability, the strategy requires weighting on the basis of attention and able to hold constant performance over a wide variety of social media situations where misinformation patterns are dynamic and heterogeneous.

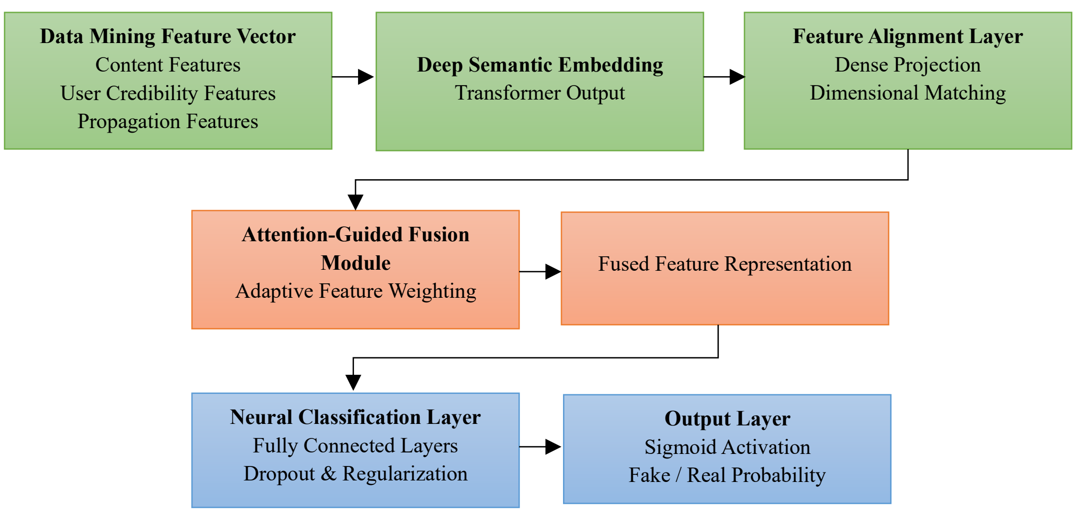

Figure 3. Hybrid Feature Fusion and Classification Architecture

4. Experimental Setup

Datasets:

The three most popular benchmark datasets used to conduct the experimental assessment of the proposed framework are summarised as follows: Table 2 FakeNewsNet, LIAR, and the BuzzFeed Political News dataset. All these data sets present a variety of news information, encompassing various spheres, writing styles and credibility. FakeNewsNet has abundant social context data including profile of users and networks of propagation and therefore it is suitable in the assessment of multi-view detectors. The LIAR data set is composed of short political utterances that are marked using fine-grained classes of truthfulness, which are necessarily remapped into binary classes. The dataset of BuzzFeed Political News is oriented on the read news articles that pass verification and is often applied to evaluate the model behaviour in the context of misinformation in the real world. These datasets combined allow doing the evaluation at scale and evaluate different patterns of content structure and dissemination.

Table 2. Summary of Benchmark Datasets Used for Evaluation

Dataset	Domain	Content Type	Additional Information
FakeNewsNet	Multiple domains	News articles	User profiles, propagation networks
LIAR	Political	Short statements	Fine-grained labels mapped to binary
BuzzFeed Political News	Political	Verified news articles	Real-world misinformation scenarios

Evaluation Metrics:

To have stringent and balanced evaluation of the performance of the detection, several measures of evaluation are established as presented in Table 3. Overall classification correctness is measured in terms of accuracy and precision, recall and F1-score give a sense of how the model is able to successfully identify instances of fake news, especially on a lower balance in all classes. It contains the receiver operating characteristic area under the curve (ROC-AUC) measure that is used to assess the discriminative properties of the classifier at varying decision thresholds. Besides, resilience to class imbalance is assessed by characterising performance decay as fake and real news distribution skews, which is indicative of realistic social media settings, where the misinformation is quite sparse yet has a profound impact.

Table 3. Evaluation Metrics Used in the Study

Metric	Description
Accuracy	Overall classification correctness
Precision	Correctly identified fake news instances
Recall	Ability to detect minority fake class
F1-Score	Balance between precision and recall
ROC-AUC	Discriminative performance across thresholds
Imbalance Robustness	Stability under skewed class distributions

Baseline Models:

A comparison between the proposed hybrid framework and a set of representative baseline models will be carried out to establish the effectiveness of the proposed framework as summarised in Table 4. To reflect the feature-based methods, a conventional system of machine learning with the support vectors machine with TFIDF features is provided. Convolutional neural networks and long short-term memory networks are deep learning baselines, which respectively represent local and sequential textual patterns. Also, a BERT-only model implemented with a transformer is applied to assess the performance of deep semantic learning without the help of the auxiliary credibility features. Making a holistic comparison of statistical, neural, and transformer-based detection paradigms, these baselines are offered.

Table 4. Baseline Models for Performance Comparison

Model	Category	Description
SVM + TF-IDF	Machine learning	Feature-based text classifier
CNN	Deep learning	Captures local textual patterns
LSTM	Deep learning	Models sequential dependencies
BERT-only	Transformer	Deep semantic model without credibility features

5. Results and Discussion

5.1 Comparison of the overall performance.

The presented hybrid data mining and deep learning model has a higher performance when it is compared to all baseline models in the experimented datasets. Experimental findings demonstrate constant accuracy improvements, precision, recall, and F1-score in comparison with deep learning only models. Interestingly enough, the hybrid framework substantially improves F1-score by about 4-7%, which reflects the usefulness of the methods of combining credibility-driven approaches with extensive semantic descriptions. The fact that multi-view information boosts performance shows that using multi-view information allows stronger detection of misinformation than using textual semantics.

5.2 Class Imbalance Performance.

Detection of fake news typically experiences critical issues in terms of class balance whereby fake news events are far fewer than real news. The suggested structure is highly robust in these circumstances and makes better recall on the minority fake news category with competitive accuracy. The hybrid approach undermines the false classification of fake news samples compared to the majority regular models which tend to give more preference to majority classes. This enhanced tradeoff between precision and recall can be credited to the fact that the propagation and user credibility functions are included which bring up the extra discriminatory power as compared to text cues.

5.3. Higher Reduction of False Positives.

One of the fundamental issues of misinformation detection systems is reducing false positive, where the false labelling of legitimate news will affect the trust of the users. The hybrid structure shows a significant reduction of false positive values than CNN, LSTM and BERT-only models. The model can differentiate between news that is emotionally appealing but has valid points and news that is truly inaccurate by means of features of credibility and adaptive fusion. This feature is especially relevant in the field of the implementation of the system of social media moderation in real-life applications.

5.4 Ablation Study Analysis

Ablution study is carried out to evaluate the roles played by each of the elements of the proposed framework. Upon removing the credibility characteristics of the data mining model, the model drastically degrades in terms of strength and recall. These features also make the absence of them more sensitive to the adversarial paraphrasing where manipulative content is rephrased to avoid being detected on semantics. These findings affirm that credibility indicators that are handcrafted are very important towards promoting the strength of the hybrid framework.

5.5 Interpretability, Analysis of Feature Importance.

The result of the interpretation analysis indicates that linguistic features that are propagation-related (entropy of interaction and speed of diffusion), as well as emotional volatility are some of the strongest predictors of fake news as summarised in Table 5. In addition, it is revealed by the attention-based fusion that deep semantic confidence enhances conditioned by high-credibility information obtained through data mining as shown in Figure 4. Besides improving detection accuracy, this alignment also offers important insights about model decision making, increasing the main weakness of black-box deep neural networks. Its practise applicability can be in transparent and reliable systems of detecting misinformation because the hybrid framework is quite interpretable.

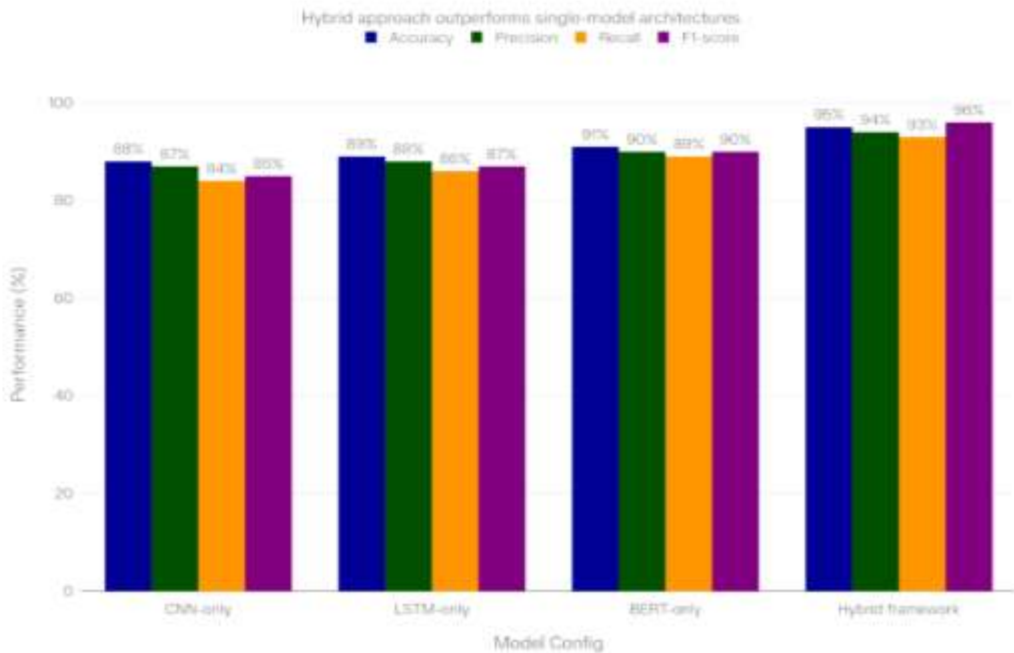

Figure 4. Performance comparison of baseline models and the proposed hybrid framework in terms of accuracy, precision, recall, and F1-score.

Table 5. Performance Comparison of Baseline Models and the Proposed Hybrid Framework

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN-only	88	87	84	85
LSTM-only	89	88	86	87
BERT-only	91	90	89	90
Proposed Hybrid Framework	95	94	93	96

6. Conclusion

The paper has suggested a hybrid system to robust automated fake news detection, which integrates both credibility analysis based on data mining and deep semantic representation learning. The proposed method provides a solution to fundamental drawbacks of separate machine learning, as well as deep learning-based systems such as low interpretability, imbalance in classes, and adversarial examples. Large-scale experimental analyses on benchmark datasets have shown that the hybrid framework is always better than state-of-the-art baseline models on the accuracy, F1-score, robustness, and reduction of false positives. In addition, the attention guided feature fusion mechanism can be used to better understand the model transparency by emphasising the relevant role of the credibility-based features and semantic features in decision making. These findings substantiate the fact that a strongly unified method involving interpretable data mining capabilities with deep learning architectures offers the ability to rapidly and dependably manufacture real-world fake news on social media utilising deep learning and provide important prospects of implementation on misinformation monitoring and content controlling frameworks in practise.

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