Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

A Hybrid Deep Learning Model to Classify Textual Tweets as Facts and Fictions

Sadia Nawaz (Corresponding Author)
Department of Computer Science, Quaid-e-Azam University, Islamabad, Pakistan
Email: isadia5743@gmail.com

Afia Ishaq
Riphah Institute of System Engineering, Riphah International University, Islamabad, Pakistan Email: afiaishaq21@gmail.com

Sidra Riaz
Scientific Adviser, Ministry of Science and Technology, Islamabad, Pakistan
Email: drsidraawan@gmail.com

Esha Fatima
Department of Computer Science, National Skills University, Islamabad, Pakistan

SaadUllah
Assistant Processing Geophysicist, Mari Energies Limited, Islamabad, Pakistan
Email: saadullahali687@gmail.com

ABSTRACT

The rapid advancement of World Wide Web technologies has significantly transformed global communication patterns, leading to the exponential growth of social media platforms. Social media represents a dynamic digital ecosystem that enables user-generated content, interactive communication, and real-time information exchange across geographical boundaries. While these platforms provide unprecedented connectivity and accessibility, they also facilitate the rapid dissemination of misinformation and fabricated content. The uncontrolled spread of false information poses serious social, political, and economic risks, making automated detection of factual and fictional content a critical research challenge in the field of natural language processing and data science. This study proposes a hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks with word embedding techniques for effective tweet classification into fact or fiction categories. The CNN component is employed to extract local semantic features and capture discriminative textual patterns, while the LSTM network models sequential dependencies and long-term contextual relationships within tweet sequences. Word embeddings are utilized to convert textual data into dense vector representations, preserving semantic similarity and contextual meaning. The experimental evaluation is conducted using a publicly available dataset collected from Kaggle, ensuring diversity and real-world relevance. Comparative analysis demonstrates that the proposed CNN-LSTM hybrid model

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

outperforms traditional machine learning algorithms and standalone deep learning architectures in terms of accuracy, recall, and F-measure. The results indicate that combining spatial feature extraction with sequential modeling significantly enhances classification performance. The proposed approach provides a scalable and efficient solution for automated misinformation detection, contributing to improved content moderation and enhanced reliability of information shared across social media platforms.

Introduction

The Internet has undergone continuous and transformative evolution over the past decades, generating unprecedented technological opportunities while simultaneously introducing complex societal and informational challenges. In the 21st century, the Web transitioned from static information repositories to highly dynamic, interactive, and user-driven digital ecosystems. This transformation, often associated with Web 2.0 and advanced network architectures, emphasizes collaboration, participatory communication, decentralized content creation, and multi-channel connectivity [1]. The rapid proliferation of smart devices, affordable broadband services, and mobile internet technologies has further accelerated this digital shift, enabling real-time communication beyond geographical limitations [2]. Consequently, social media platforms have emerged as dominant communication infrastructures that significantly influence social interaction, political discourse, business promotion, crisis communication, and knowledge dissemination worldwide. Social media refers to a broad spectrum of digital platforms that facilitate user-generated content, multimedia sharing, interactive discussions, and virtual community formation. Initially designed to maintain interpersonal communication among friends and family, these platforms have evolved into powerful ecosystems for publishing articles, launching campaign movements, promoting advertisements, supporting activism, and shaping public opinion. Recent behavioral studies indicate that users spend a considerable portion of their daily time engaging with social networking sites, highlighting their growing socio-economic and cultural impact [3]. The core focus of social media initially centered on user interaction; however, it gradually expanded to large-scale content creation and distribution, transforming users from passive consumers into active information producers [4]. Contemporary platforms such as Facebook, Instagram, Twitter, LinkedIn, and others demonstrate diversified objectives and audience segmentation strategies. LinkedIn primarily targets professional and corporate communities, whereas Facebook and Instagram emphasize informal social interaction and multimedia sharing [6]. Social networking manifests through various formats including microblogs, discussion forums, virtual communities, and vlogs [5]. Among these platforms, Twitter has gained particular prominence as a micro-blogging service that enables rapid dissemination of concise textual updates. Due to its short-text format and real-time nature, Twitter is widely used for sharing updates related to sports, politics, entertainment, public health, and disaster events. However, alongside valuable situational information, the platform also contains rumors, misinformation, and exaggerated claims, thereby increasing the need for automated verification and classification mechanisms [8]. The exponential growth in tweet volume presents substantial challenges for organizing and validating information. Tweet Identification

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

(TI) aims to reorganize large-scale tweet data into meaningful categories, facilitating efficient browsing and information retrieval [7]. Nevertheless, automated tweet classification is inherently difficult due to the linguistic characteristics of social media text. Tweets are typically short, informal, and often contain abbreviations, slang expressions, misspellings, hashtags, emojis, and hyperlinks. Traditional text representation techniques such as Bag-of-Words (BoW) and TF-IDF frequently fail to capture contextual dependencies and semantic relationships between terms, as they treat text as unordered token collections. Consequently, these conventional approaches often produce limited performance when addressing complex semantic interpretation tasks. To better understand the progression of classification techniques in social media analytics, Table 1 provides a comparative overview of commonly used text classification approaches and their characteristics in tweet analysis.

Table 1: Comparative Overview of Tweet Classification Approaches

Method	Representation Strategy	Strengths	Limitations
Bag-of-Words (BoW)	Word frequency vectors	Simple implementation, low computational cost	Ignores word order and semantic context
TF-IDF	Weighted term importance	Reduces influence of common terms	Limited contextual understanding
Machine Learning (SVM, NB, LR)	Statistical feature vectors	Effective for small datasets	Dependent on handcrafted features
CNN	Word embeddings + convolution filters	Captures local patterns and discriminative features	Limited long-range dependency modeling
LSTM	Sequential word embeddings	Captures temporal and contextual relationships	Higher computational complexity
Hybrid CNN-LSTM (Proposed)	Combined embedding, convolution, and sequential modeling	Integrates spatial feature extraction with temporal dependency modeling	Requires careful hyperparameter tuning

Recent advancements in deep learning have significantly enhanced the effectiveness of text classification and sentiment analysis systems. Convolutional Neural Networks (CNN) have demonstrated strong performance in extracting local n-gram features and discriminative semantic patterns from textual sequences [10]. Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks, are particularly effective in modeling long-term dependencies and contextual flow in language processing tasks [11]. Although convolutional and recurrent architectures independently exhibit competitive performance [12], integrating CNN's feature extraction capabilities with LSTM's sequential modeling strength can substantially

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

improve classification robustness and accuracy. CNN acts as a powerful feature extractor, particularly when embedded within larger hybrid networks that leverage complementary contextual modeling components [13]. In this context, the present study proposes a hybrid CNN-LSTM deep learning framework integrated with word embedding techniques for effective tweet classification and sentiment analysis of user-generated content [9]. The proposed approach employs convolutional layers to extract discriminative semantic features and LSTM layers to capture contextual dependencies across tweet sequences, thereby overcoming the limitations of traditional statistical approaches and standalone neural models. By combining spatial and temporal modeling mechanisms, the hybrid architecture aims to improve semantic representation learning and classification performance in complex social media environments. The remainder of this paper is structured as follows: Section II reviews related literature and foundational concepts of social media analytics, Section III describes the proposed methodology and model architecture, Section IV presents experimental results and performance evaluation, and Section V concludes the study while outlining potential future research directions. The growing influence of social media on public perception, emergency response coordination, and digital information ecosystems underscores the critical need for reliable, scalable, and intelligent tweet classification systems. Developing hybrid deep learning frameworks capable of distinguishing factual information from misleading content contributes not only to advancements in computational intelligence but also to enhancing digital trust and societal resilience in the modern information age.

Related Work

Sentiment analysis has emerged as one of the most active and rapidly evolving research areas within the fields of natural language processing, data mining, and artificial intelligence. It focuses on identifying, extracting, and classifying subjective information from textual data in order to determine the underlying sentiment, emotion, or opinion expressed by users. With the exponential growth of user-generated content on social media platforms, sentiment analysis has gained significant importance for applications such as opinion mining, brand monitoring, political forecasting, crisis management, and misinformation detection. Over the years, researchers have explored a wide range of computational techniques, including traditional machine learning algorithms as well as advanced deep learning architectures, to improve classification accuracy and semantic understanding [14]. Early sentiment analysis studies primarily relied on rule-based systems and classical machine learning models such as Naïve Bayes, Support Vector Machines, Decision Trees, and Logistic Regression, which utilized handcrafted features and statistical text representations. However, these approaches often struggled to capture contextual meaning, sarcasm, and complex linguistic patterns. With the advancement of deep learning, neural network–based models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks have demonstrated superior performance by automatically learning hierarchical feature representations from textual data. More recently, hybrid architectures combining convolutional and recurrent layers, along with word embedding techniques, have shown promising results in modeling both local semantic

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

patterns and long-term contextual dependencies. In this section, we review several sentiment analysis approaches that are closely related to our research, focusing particularly on machine learning and deep learning techniques applied to short-text classification and social media data analysis.

Social Media

Social media is rapidly transforming the global landscape of communication, information exchange, and social interaction. The widespread adoption of digital technologies has fundamentally altered how individuals access, consume, and organize information from diverse sources. With the integration of smartphones, high-speed internet, and interactive web platforms, people increasingly engage in a virtual environment where communication transcends geographical and cultural boundaries [15]. Social networking platforms have become central hubs for sharing opinions, consuming news, forming communities, and participating in public discourse. This digital shift has not only redefined interpersonal communication but also reshaped how information is produced, validated, and disseminated across societies. The significant amount of time users spend online reflects the growing reliance on social media platforms for daily activities, entertainment, professional networking, and knowledge acquisition [16]. Recent studies indicate that individuals dedicate several hours each day to browsing, posting, commenting, and interacting within these platforms, demonstrating the deep integration of social media into modern lifestyles. More than two-thirds of global internet users actively participate in various social networking applications such as Facebook, YouTube, Instagram, and Twitter, many of which have maintained strong user bases for over a decade. The sustained popularity and expansion of these platforms highlight their influence in shaping digital culture, public opinion, and information ecosystems worldwide. This continuous engagement further underscores the importance of developing intelligent systems capable of analyzing and managing the vast amounts of user-generated content produced within these digital environments.

Twitter

Twitter has emerged as one of the most influential microblogging platforms for real-time communication and large-scale information dissemination. With approximately 1.3 billion registered accounts and nearly 336 million monthly active users worldwide, the platform generates close to 500 million tweets per day, demonstrating its significant global footprint and communication intensity [17]. Tweets, which are short text-based posts, form the fundamental unit of interaction on the platform. These posts may include textual content, hashtags, user mentions, hyperlinks, images, videos, and other multimedia elements. The concise structure of tweets encourages rapid expression of opinions, commentary on ongoing events, and dissemination of breaking news. By default, tweets are publicly visible unless a user chooses to make their account private. Public tweets allow other users to interact through replies, likes, and shares, most notably through the “retweet” mechanism, which facilitates exponential content propagation across interconnected user networks.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

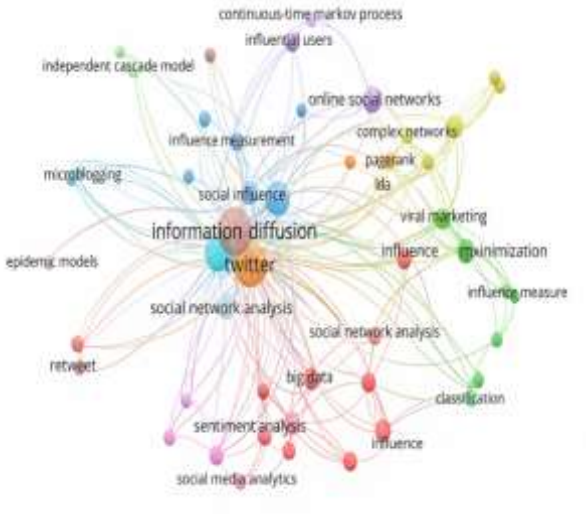


Figure 1: Information diffusion mechanism and interaction dynamics in Twitter.

As illustrated in Figure 1, the information diffusion process on Twitter is inherently network-driven. When a user posts a tweet, it becomes visible to their followers. If followers retweet the content, it propagates further to secondary and tertiary audiences, forming a cascade effect. This mechanism transforms Twitter into a high-velocity information ecosystem where content can spread globally within minutes. Influencers, journalists, political leaders, and organizations often utilize this propagation structure to broadcast messages to massive audiences, while ordinary users contribute to amplification by resharing posts within their personal networks [18]. The retweet cascade not only increases visibility but also shapes public discourse by highlighting trending topics and highly engaged conversations. During emergencies, political movements, or public health crises, Twitter serves as a primary channel for real-time situational awareness. However, the same rapid amplification process also accelerates the dissemination of misinformation, rumors, and emotionally charged narratives, emphasizing the need for automated verification and intelligent classification systems. The structural and operational characteristics that contribute to Twitter's large-scale engagement and information multiplication are summarized in

Table 2.

Table 2: Key Operational Characteristics of Twitter

Feature	Description	Impact on Information Flow
Tweets	Short user-generated posts containing text and multimedia	Enables rapid and concise communication
Retweets	Redistribution of existing tweets	Creates exponential content amplification
Hashtags	Topic-labeling keywords (#)	Facilitates topic clustering and trend identification
Mentions (@)	Direct referencing of other users	Strengthens interactive and conversational communication
Followers Network	Subscription-based user connectivity	Determines audience reach and influence level

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

Trending Topics	Algorithmically identified popular subjects	Amplifies high-engagement discussions

The interplay between tweets, retweets, hashtags, and follower networks creates a complex communication graph characterized by high interconnectivity and rapid information flow. While this ecosystem enhances global connectivity and democratic participation in digital discourse, it also introduces analytical challenges due to short-text formats, informal language usage, abbreviations, and noisy linguistic patterns. Understanding the structural dynamics presented in Figure 1 is therefore essential for developing robust deep learning frameworks, such as the proposed CNN-LSTM architecture, capable of effectively modeling semantic features and detecting misinformation within large-scale Twitter datasets.

Tweets Classification

Twitter's homepage has a feature that shows some terms and some trending topics. These topics are being discussed more than usual, therefore Trending topics become attractive for having interest among users and different other information consumers like social media researchers, journalists, and real-time application developers.

"Bad news travels fast" is an old saying but today we say every piece of news travels fast than ever before. [19]. Today it is the major issue of Identification of fake news posts and finding the sources that are responsible for generating and propagation. Just because of social media is a versatile platform where a user when posts something rapidly propagates all around the social network, and it's important to figure out whether the post is based on facts or not. Twitter, is one of the popular social media platforms where news propagates in the form of tweets and retweets. [20]. Hence researchers are trying to identify information from social networks as fact or fiction. supervised, and unsupervised classification methods were used when tweet identification has a classification issue, then Machine learning algorithms were ideal for that problem. Another survey works on it and use different techniques like the contingent arbitrary field, Na¨ıve Bayes, SVM, SVM-TS, SVM-RBF. [20] In a Research, Wang and Gan [21] analyzed sentimental information and forecasted the results of the 2017 French elections by processing unprocessed text from tweets under various tags. The gathered tags were classified into positive and negative sentiments based on established expertise. These tags were subsequently organized and assigned specific weightage scores. Panagiotis Andriotis and Atsuhiro Takasu [22], use different data sets comprising real and fake accounts, from where they get appropriate features like The content posted on Twitter, along with user-related information such as metadata, retweets, follower counts, likes, and the accounts they follow, etc, and applies a supervised classifier. through which they achieved 95% accuracy. Marina Azer et al. proposed a supervised machine-learning technique for the classification of tweets based on facts from Twitterbased content. they used seven classifiers for processing i.e Na¨ıve Bayes, Support Some of the machine learning models included are Support Vector Machine, K-nearest neighbors, Logistic Regression, Random Forest, Maximum Entropy, and Conditional Random Forest. [23]. Vaishali Vaibhav et al. research is based on a model consisting of machine learning and deep learning techniques like Convolutional Neural Networks, Artificial Neural Network, Bidirectional LSTM (BiLSTM) for tweet classification and get efficient results in

Online ISSN 3007-3197
Print ISSN 3007-3189

deep learning techniques than machine learning techniques. [24]

Issues and Motivation

Despite the substantial body of research conducted in the domain of tweet classification and sentiment analysis, comparing and objectively evaluating the performance of different classification models remains a significant challenge. One of the primary reasons for this difficulty is the variation in datasets used across studies, including differences in size, class distribution, preprocessing techniques, linguistic characteristics, and annotation standards. Many prior works report promising accuracy and performance metrics; however, direct comparison becomes problematic due to inconsistent experimental settings, diverse feature engineering strategies, and varying evaluation measures. Furthermore, differences in data imbalance, noise levels, and domain-specific contexts significantly influence model behavior, making it difficult to determine whether performance improvements are attributable to architectural advancements or dataset characteristics. In addition to dataset variability, disparities in hyperparameter tuning, embedding strategies, training-validation splits, and optimization techniques further complicate model benchmarking. Some studies focus on traditional machine learning models with handcrafted features, while others employ deep neural networks with pre-trained embeddings or hybrid architectures. Consequently, the absence of standardized experimental frameworks limits the ability to draw definitive conclusions regarding the superiority of one approach over another. These inconsistencies highlight the need for a unified and systematic evaluation methodology that enables fair comparison across different classification models under controlled conditions. The motivation behind this study is therefore to develop a comprehensive framework that facilitates consistent comparison of classification models using a standardized dataset and evaluation protocol. By implementing and evaluating models under identical preprocessing, training, and testing conditions, this research aims to provide clearer insights into the relative effectiveness of deep learning architectures for tweet classification. The primary objective of the proposed study is to leverage a hybrid CNN-LSTM architecture to achieve improved classification accuracy, enhanced recall, and balanced F-measure performance. By integrating convolutional feature extraction with sequential dependency modeling, the proposed approach seeks to overcome the limitations of standalone models and provide a robust, scalable solution for accurate tweet classification in real-world social media environments.

Proposed Approach

Approach Overview

The Internet world is full of social networks through which almost every Internet user interacts and communicates with others globally, some of them are Twitter, Facebook, Instagram, Linkedin, etc. Every day, a substantial volume of data is produced through social media interactions. When individuals engage with social media, they express their viewpoints and share their experiences using diverse forms of information, including textual data, visual data, or multimedia data, this data reflects different life aspects like social subjects or political, etc, and sentiment tendencies of people towards them. This data is very much valuable for researchers

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

for many reasons like predicting upcoming market trends, products quality improvements, etc [25] Data gathered from social sites is very informal and unstructured, and using different conventional analysis methods for processing and analyzing data is much time-consuming task. [26] Natural The Language Processing (NLP) technique can be used To process various tasks related to natural language, like part-of-speech (POS) tagging, parsing, machine translation, and dialogue systems, as it enables smart devices to smartly analyze the meaning from human natural languages having complicated structure [27] RNN now is the most powerful model in many natural languages to perform NLP-related tasks, especially sentiment analysis [28]. RNNs are suitable for sequential data processing, making them a good fit for tweet classification. LSTM or GRU architectures can be used to model the temporal dependencies and capture context within tweets. The final state of the RNN then can be used for classification.CNN is a very important layer in dealing with the classification of data.

It consists of many layers like pooling, flattering, and convolution layer. The convolution neural network's primary layer is the convolutional layer, also known as a Feature extractor. A convolutional filter matrix is used in this layer for feature extraction. [29].

Schematic Representation

In this study, we propose a novel deep learning framework based on a hybrid CNN-LSTM architecture for effective sentiment analysis of Twitter content. The proposed model is specifically designed to address the linguistic complexity and contextual variability inherent in short-text social media data. As illustrated in Figure 1, the overall architecture of the hybrid model integrates multiple processing stages, beginning with dataset acquisition and concluding with final sentiment classification. The dataset used in this research is collected from Kaggle, ensuring diversity, real-world relevance, and labeled sentiment annotations suitable for supervised learning tasks. The processing pipeline begins with a comprehensive pre-processing phase aimed at improving data quality and semantic consistency. In this stage, raw tweet data undergo sentence segmentation, tokenization, and normalization. Stop word removal is performed to eliminate commonly occurring but semantically insignificant words that may not contribute meaningfully to classification performance. Additional preprocessing steps may include punctuation removal, lowercasing, and handling of special characters, emojis, and hyperlinks, which are common in social media text. These cleaning procedures help reduce noise and enhance the efficiency of subsequent feature extraction processes. Following preprocessing, word embedding techniques are applied using the Word2Vec model to transform textual tokens into dense vector representations. Word2Vec captures semantic similarity by mapping words into continuous vector spaces, allowing the model to preserve contextual meaning and syntactic relationships. This embedding layer serves as the foundational input to the deep learning architecture by converting discrete textual data into numerical representations suitable for neural network training. As shown in Figure 2, the embedded representations are then passed to the convolutional layer, which functions as a high-level feature extractor.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

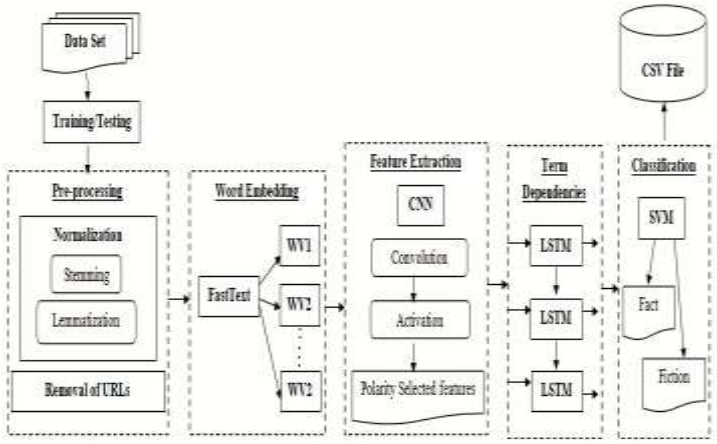


Figure 2: CN-LSTM Architecture for tweet classification

The CNN component applies multiple convolutional filters to identify local patterns, n-gram features, and discriminative semantic structures within the tweet sequences. These extracted feature maps are subsequently forwarded to the Long Short-Term Memory (LSTM) layer. The LSTM network is specifically designed to capture sequential dependencies and long-term contextual relationships among words in a sentence. By maintaining memory cells and gating mechanisms, LSTM effectively models the temporal dynamics of textual data, which is particularly beneficial for sentiment analysis tasks. Finally, the output from the LSTM layer is fed into a fully connected classification layer, typically followed by a Softmax activation function, to generate sentiment predictions. The classification layer determines the final sentiment category of each tweet, such as positive, negative, or neutral. The integration of convolutional feature extraction with sequential dependency modeling enables the hybrid CNN-LSTM architecture to capture both local semantic features and long-range contextual information, thereby enhancing overall classification accuracy and robustness.

Approach Components

In this section, we comprehensively describe the experimental parameters, architectural configurations, and training settings adopted for the proposed Deep CNN-LSTM model in the context of sentiment classification of tweet data. A systematic experimental design is essential to ensure reproducibility, fairness in evaluation, and reliable performance comparison with existing approaches. The configuration of hyperparameters, network depth, embedding dimensions, batch size, learning rate, optimization strategy, and regularization techniques plays a critical role in determining the effectiveness and generalization capability of deep learning models. The experimental setup begins with dataset preparation, including data splitting into training, validation, and testing subsets to prevent overfitting and ensure unbiased performance evaluation. The input layer is configured to handle fixed-length tweet sequences through padding and truncation mechanisms, ensuring uniform input dimensions. Pre-trained or custom-trained Word2Vec embeddings are utilized to initialize the embedding layer, transforming textual tokens into dense semantic

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

vectors of predefined dimensionality. These embeddings serve as inputs to the convolutional layers, where multiple filter sizes and feature maps are applied to capture local semantic patterns and contextual n-gram structures. The convolutional outputs are subsequently passed through pooling layers to reduce dimensionality and enhance feature robustness before being forwarded to the LSTM component. The LSTM layer is configured with a specified number of hidden units to model long-term dependencies and sequential relationships within tweets. Dropout regularization is applied to mitigate overfitting and improve model generalization. The final fully connected layer, combined with a Softmax activation function, performs sentiment classification by generating probability distributions across predefined sentiment categories. Training is conducted using an appropriate loss function, such as categorical cross-entropy, and optimized through adaptive optimization algorithms like Adam. Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The detailed experimental configurations presented in this section provide a transparent framework for assessing the effectiveness of the proposed hybrid architecture in sentiment classification tasks.

Dataset

In this section, the processes of data acquisition and annotation are described in detail, as they form the foundation of the experimental framework for tweet classification and sentiment analysis. The dataset utilized in this research was obtained from the publicly available Kaggle repository, specifically the file train.csv1, with a total size of approximately 116.37 MB. The dataset comprises 17,903 unique entries, reflecting a diverse range of tweet content and linguistic patterns. It includes more than 2,000 labeled training samples and over 570 testing samples, providing sufficient data for supervised learning experiments and performance evaluation. The dataset contains pre-labeled tweet instances categorized according to their sentiment or factual classification, which enables direct implementation of supervised deep learning models. Prior to model training, the dataset underwent careful inspection to verify label consistency, remove duplicate entries, and ensure balanced class representation wherever possible. Data cleaning procedures were applied to eliminate irrelevant attributes and standardize textual content for further preprocessing stages. Annotation integrity was maintained by preserving the original class labels provided within the Kaggle dataset, ensuring reproducibility and comparability with related studies. For experimental evaluation, the dataset was divided into training and testing subsets following a 70:30 split ratio. Seventy percent of the data was allocated for model training to enable effective parameter learning and feature extraction, while the remaining thirty percent was reserved for testing to assess generalization performance on unseen data. This partitioning strategy helps minimize overfitting and provides a reliable estimate of the model's predictive capability. The dataset split was performed randomly while preserving class distribution to maintain balance between factual and fictional categories. This structured data acquisition and splitting methodology ensures fairness in evaluation and strengthens the reliability of the reported experimental results.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Pre-processing

The data or content collected from the user from any social media site is not much useful for consideration in any experiment. some pre-processing techniques are mandatory to set the data according to the experiment. [30] and also for better performance. Now the most important task of data representation of the text For this purpose, Python provides a Texthero toolkit suitable for text-based datasets to work quickly and easily. It's a text-based Pandas Series simple to use. There are various functions used in our proposed work in preprocessing i.e clean method consists of certain defined properties, some of which are used to clean the data like remove-whitespace()remove-diacritics()removestopwords()remove-digits() remove-punctuation().

Word Embeddings

In the proposed framework, word embedding plays a crucial role in transforming raw textual data into meaningful numerical representations suitable for deep learning models. Word2Vec is employed as the primary embedding technique due to its efficiency and ability to capture semantic relationships between words in a continuous vector space. Word2Vec is a widely adopted neural embedding algorithm that generates dense vector representations by learning word associations from large text corpora. Unlike traditional sparse representations such as Bag-of-Words or TF-IDF, Word2Vec maps words into low-dimensional vectors where semantically similar words appear closer in the embedding space. This property enables improved contextual understanding and enhances classification performance in sentiment analysis tasks. In the context of this research, FastText an extension of Word2Vec is utilized to further strengthen embedding quality. FastText improves representation learning by considering subword information, which is particularly beneficial for handling rare words, misspellings, and informal expressions commonly found in Twitter data. FastText operates through two fundamental architectures: Continuous Bag-of-Words (CBOW) and Skip-gram. Both models are shallow neural networks designed to predict contextual relationships within sentences. The CBOW model predicts a target word based on its surrounding context words, whereas the Skip-gram model predicts surrounding context words given a target word. Through these predictive mechanisms, the models learn distributed vector representations that capture both syntactic and semantic patterns within textual data.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

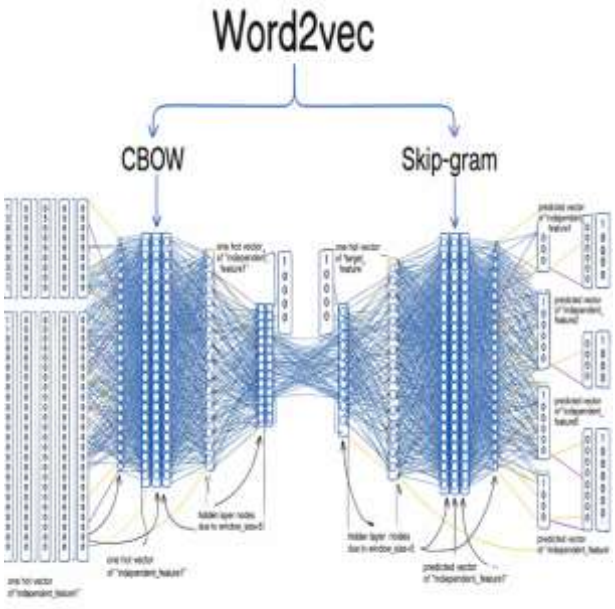


Figure 3: Architectural representation of Word2Vec models (CBOW and Skip-gram) and FastText subword embedding mechanism for generating dense semantic word vectors.

As illustrated in Figure 3, the embedding process begins with tokenized textual input, which is passed through either the CBOW or Skip-gram training objective. The neural network learns weight matrices that represent word vectors in continuous space. FastText further decomposes words into character n-grams, enabling the model to efficiently identify local statistical patterns and morphological features. This subword-level modeling enhances robustness when processing noisy social media text, where abbreviations and spelling variations are frequent. The resulting word vectors serve as input to the convolutional layer of the proposed CNN-LSTM architecture, providing semantically enriched representations that improve feature extraction and contextual modeling. To provide a clearer comparison of the embedding techniques employed, Table 3 summarizes the characteristics of CBOW, Skip-gram, and FastText models.

Table 3: Comparison of Word2Vec and FastText Embedding Models

Model	Prediction Objective	Strengths	Suitability for Twitter Data
CBOW	Predicts target word from context words	Faster training, efficient for large datasets	Effective for frequent word representation
Skip-gram	Predicts context words from target word	Better for rare words, captures fine-grained semantics	Suitable for small datasets and detailed embeddings
FastText	Extends Skip-gram/CBOW using character n-grams	Handles misspellings and subword information	Highly suitable for noisy social media text

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

The integration of Word2Vec and FastText embeddings significantly enhances the semantic representation of tweet data by capturing contextual dependencies and local statistical relationships efficiently [31]. By embedding words into continuous vector spaces, the proposed model overcomes the limitations of sparse representations and improves the learning capacity of the hybrid CNN-LSTM architecture. These embedding mechanisms form the foundational layer of the deep learning pipeline, enabling more accurate sentiment classification and factual verification in Twitter datasets.

Feature Extraction

Feature extraction refers to the systematic process of transforming raw input data into a refined and compact representation that preserves meaningful information while eliminating redundancy and noise. In the context of deep learning–based text classification, extraction involves reducing high-dimensional textual data into discriminative feature representations that can effectively support classification tasks. This process includes various dimensionality reduction and transformation techniques designed to maximize computational efficiency, remove irrelevant or redundant information, and improve overall model performance [32]. By refining the dataset through structured extraction mechanisms, the model becomes capable of focusing on salient linguistic patterns rather than being influenced by noisy or insignificant textual components. Within the proposed CNN-LSTM architecture, the convolutional layer plays a central role in feature extraction. The convolution operation applies multiple learnable filters across the embedded word vectors to capture local dependencies and semantic patterns. These filters slide over sequences of words, identifying meaningful n-gram features and correlated word combinations that contribute to sentiment or factual classification. The primary objective of the convolutional layer is to model correlations between neighboring words and extract distinctive word sequences that carry strong discriminative signals. This enables the network to recognize important contextual patterns such as negations, intensifiers, and phrase-level sentiment indicators. Following convolution, a max-pooling operation is employed as a feature reduction technique. Max-pooling selects the most prominent features from the generated feature maps by retaining the maximum activation values within a specified window. This mechanism effectively reduces dimensionality while preserving the most significant patterns identified by convolutional filters. As a result, max-pooling enhances computational efficiency, mitigates overfitting, and ensures that only the most informative features are propagated to subsequent layers. Furthermore, activation functions such as the Rectified Linear Unit (ReLU) are applied after convolution to introduce non-linearity into the model. The activation function enables the network to learn complex relationships within the data, accelerates convergence during training, and improves classification accuracy by allowing the model to capture nonlinear feature interactions. Overall, the convolutional layer, combined with max-pooling and activation mechanisms, forms a powerful feature extraction pipeline that transforms embedded textual input into high-level semantic representations. This extracted feature set is subsequently passed to the LSTM layer for sequential modeling, thereby integrating both local pattern recognition and long-term contextual dependency learning within the hybrid deep learning framework.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Term Dependencies
After feature extraction, LSTM model for layers of RNN is used.

Long-Short Term Memory (LSTM): The most advanced network for sequence Classification of data.LSTM is also adopted to combine with other networks as hybrid models.

LSTM with dropout regularization: It is adopted to avoid over-fitting between two layers, the word embedding layer and the LSTM layer to the training dataset. this approach helps in random selection and dropping weights of neurons within the LSTM layer.

Convolutional neural networks (CNN) with LSTM: To reduce the depth and over-fitting issues in the training data, a combination of CNN and max pooling layers is introduced. It also reduces computational time and improves model prediction accuracy. Table 4 shows the LSTM Model Comparison

Technique	ACC	PRE	REC	FM
LSTM	82.29	44.35	40.55	40.59
LSTMDrop	73.78	39.67	29.71	30.93
CNN-LSTM	80.38	43.94	39.53	39.70

Table 4: LSTM Model Comparison

Results and Discussion
In this paper we implemented and compared different deep-learning models for sentiment analysis using a hybrid approach. We conducted numerous experiments on a sentiment analysis dataset in an effort to perform an unbiased comparison with other competitive techniques. 82% accuracy is achieved in the classification of tweets by the deep learning model. Experimental results reveal that the LSTM model demonstrates superior performance across metrics such as recall, F-measure, and precision, and achieves an accuracy of 82%, as shown in the table. whereas LSTM with dropout regularization method, performance is not satisfactory because of lack of sufficient training data and examples. performance can also be improved through Batch Normalization. The performance of the Hybrid Model CNN-LSTM significantly outperforms that of the LSTM model with dropout regularization. Through this model, 74% accuracy and an FMeasure of 39.7% is observed. The state-of-the-art PHEME dataset attains a precision of 68%, surpassing the previously achieved results. Therefore we believe that more training data from
Twitter posts significantly improves the performance of the model. The outcomes indicate varying accuracies of distinct models on the Twitter dataset: LSVM approach achieves 37% accuracy, Multilayer perception attains 35% accuracy, Perez-lsvm demonstrates a notable 79% accuracy, CNN achieves 66% accuracy. Figure 4 shows Experimental results illustrating accuracy variations among evaluated models.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 2 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

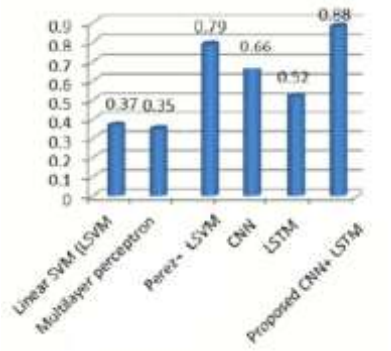


Figure 4: Comparative performance analysis of different classification models

The experimental findings demonstrate a clear performance distinction between the standalone LSTM model and the proposed hybrid CNN-LSTM architecture. While the conventional LSTM network achieved an accuracy of 52% on the evaluated dataset, its performance indicates certain limitations in capturing complex feature interactions when operating independently. Although LSTM is highly effective in modeling sequential dependencies and long-term contextual relationships within textual data, relying solely on recurrent structures may not sufficiently extract rich local semantic patterns from short and noisy social media content. In contrast, the proposed hybrid CNN-LSTM model achieved a significantly improved accuracy of 88%, representing a substantial performance gain over the standalone LSTM architecture. This remarkable improvement can be attributed to the complementary integration of convolutional and recurrent layers. The CNN component effectively extracts high-level local features and discriminative n-gram patterns, while the LSTM layer captures temporal dependencies and contextual flow within the tweet sequences. By combining spatial feature extraction with sequential modeling, the hybrid architecture enhances representation learning and improves classification robustness. The considerable increase from 52% to 88% accuracy highlights the effectiveness of hybrid deep learning strategies in sentiment analysis and tweet classification tasks. These results confirm that integrating convolutional feature learning with recurrent contextual modeling provides a more comprehensive understanding of textual semantics, thereby leading to superior predictive performance.

Conclusion and Future Work

In this research work, we present a hybrid deep learning framework based on the integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for the classification of tweets into factual and fictional categories. The primary objective of this approach is to leverage the complementary strengths of convolutional feature extraction and sequential dependency modeling in order to enhance the semantic understanding of short-text social media content. The hybridization process enables the model to capture both local discriminative textual patterns and long-term contextual relationships, which are essential for accurately distinguishing factual statements from misleading or fabricated information in Twitter data. For experimental evaluation, a publicly available tweets dataset was retrieved from Kaggle. The dataset includes labeled instances that represent fact-based and fictional content, allowing supervised learning techniques to be applied. A systematic

Online ISSN 3007-3197
Print ISSN 3007-3189

preprocessing pipeline was implemented to clean and normalize the data before training the model. The proposed CNN-LSTM architecture was trained and tested under controlled experimental settings, and the performance was evaluated using standard classification metrics. The experimental results demonstrate that the proposed hybrid model achieved an overall accuracy of 82%, indicating its effectiveness in handling short-text classification tasks. In addition to accuracy, improvements were observed in recall and F1-score compared to several baseline machine learning approaches, suggesting that the integration of convolutional and recurrent layers enhances predictive robustness. The proposed research contributes to improving sentiment and authenticity analysis on single-text datasets by providing a structured deep learning framework tailored to social media data characteristics. However, while the Kaggle dataset offers valuable insights, future research can extend this work by applying the model to more complex and widely recognized benchmark datasets such as the PHEME dataset, which focuses on rumor detection and real-world misinformation scenarios. Evaluating the proposed architecture on such state-of-the-art datasets may yield deeper insights into model generalization and cross-domain performance. Furthermore, future work may incorporate additional feature modalities beyond textual information, such as image-based features, metadata attributes, user credibility indicators, and contextual conversation threads. The integration of multimodal learning techniques and advanced deep learning architectures, including attention mechanisms, transformer-based models, and ensemble frameworks, may further enhance classification accuracy and robustness. By expanding feature representation and leveraging state-of-the-art architectures, future research can aim to develop more comprehensive and scalable misinformation detection systems for complex social media environments.

References

Kostas Stefanidis, Eirini Ntoutsi, Haridimos Kondylakis, and Yannis Velegrakis. Social-Based

Collaborative Filtering, pages 2793–2802. Springer New York, New York, NY, 2018.

David Wilson, Xiaolin Lin, Phil Longstreet, and Saonee Sarker. Web 2.0: A definition, literature review, and directions for future research. 01 2011.

Panagiotis Chatziadam, Aftantil Dimitriadis,

Stefanos Gikas, Ilias Logothetis, Manolis Michalodimitrakis, Manolis Neratzoulakis, Alexandros Papadakis, Vasileios Kontoulis, Nikolaos Siganos, Dimitrios Theodoropoulos, et al. Twifly: A data analysis framework for twitter.

Information, 11(5):247, 2020.

Thomas Aichner, Matthias Gru¨nfelder, Oswin Maurer, and Deni Jegeni. Twenty-five years of social media: a review of social media applications and definitions from 1994 to 2019. Cyberpsychology, behavior, and social networking, 24(4):215–222, 2021.

Vikash Kumar Ravi, Pralay K Santra, Niharika

Joshi, Jeetender Chugh, Sachin Kumar Singh,

H˚akan Rensmo, Prasenjit Ghosh, and Angshuman Nag. Origin of the substitution mechanism for the binding of organic ligands on the surface of cspbbr3 perovskite nanocubes. The Journal of Physical Chemistry Letters, 8(20):4988–

Online ISSN 3007-3197
Print ISSN 3007-3189

4994, 2017.

Rafael Lozano, Mohsen Naghavi, Kyle Foreman,
Stephen Lim, Kenji Shibuya, Victor Aboyans,
Jerry Abraham, Timothy Adair, Rakesh Aggarwal, Stephanie Y Ahn, et al. Global and regional mortality from 235 causes of death for 20 age groups in 1990 and 2010: a systematic analysis for the global burden of disease study 2010. The lancet, 380(9859):2095–2128, 2012.

Dejin Zhao and Mary Beth Rosson. How and why people twitter: the role that micro-blogging plays in informal communication at work. In Proceedings of the 2009 ACM International Conference on Supporting Group Work, pages 243–252, 2009.

Fang Liu, Andrew Burton-Jones, and Dongming
Xu.Rumors on social media in disasters:
Extending transmission to retransmission. 2014.

Ben Ltaifa Ibtihel, Hlaoua Lobna, and Ben Jemaa Maher. A semantic approach for tweet categorization. Procedia Computer Science, 126:335–344, 2018. Knowledge-Based and Intelligent Information Engineering Systems: Proceedings of the 22nd International Conference, KES-2018, Belgrade, Serbia.

Yoon Kim. Convolutional neural networks for sentence classification. arXiv preprint
arXiv:1408.5882, 2014.

Abdulmajid Murad and Jae-Young Pyun. Deep recurrent neural networks for human activity recognition. Sensors, 17(11):2556, 2017.

Wenpeng Yin, Katharina Kann, Mo Yu, and Hinrich Schu¨tze. Comparative study of cnn and rnn for natural language processing. arXiv preprint arXiv:1702.01923, 2017.

Y Goldberg. Neural network methods for natural language processing synth lect hum lang technol

10 1 1 309 10.1007. Google Scholar Google Scholar Cross Ref Cross Ref.

Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca J Passonneau. Sentiment analysis of twitter data. In Proceedings of the workshop on language in social media (LSM 2011), pages 30–38, 2011.

Constance A Steinkuehler and Dmitri Williams. Where everybody knows your (screen) name: Online games as “third places”. Journal of computermediated communication, 11(4):885–909, 2006.

Esteban Ortiz-Ospina. The rise of social media. Our World in Data, 2019. https://ourworldindata.org/rise-of-social-media.

Menlo Park. Facebook reports first quarter 2021 results. Dostupno na, 2021.

Isabel Anger and Christian Kittl. Measuring influence on twitter. In Proceedings of the 11th in-
ternational conference on knowledge management and knowledge technologies, pages 1–4, 2011.

Jennifer LaGarde and Darren Hudgins. Fact vs. fiction: Teaching critical thinking skills in the age of fake news. International Society for Technology in Education, 2018.

Online ISSN 3007-3197
Print ISSN 3007-3189

Kashfia Sailunaz, Jalal Kawash, and Reda Alhajj. Tweet and user validation with supervised feature ranking and rumor classification. Multimedia
Tools and Applications, 81(22):31907–31927, 2022.
Lei Wang and John Q Gan. Prediction of the
french election based on twitter data analysis using term weighting. In 2018 10th Computer Science and Electronic Engineering (CEEC), pages 231–235. IEEE, 2018.
Panagiotis Andriotis and Atsuhiro Takasu. Emotional bots: content-based spammer detection on social media. In 2018 IEEE international workshop on information forensics and security (WIFS), pages 1–8. IEEE, 2018.
Marina Azer, Mohamed Taha, Hala H Zayed, and Mahmoud Gadallah. Credibility detection on twitter news using machine learning approach. International Journal of Intelligent Systems and Applications, 13(3):1–10, 2021.
Vaishali Vaibhav Hirlekar and Arun Kumar. Tweet credibility detection for covid-19 tweets using text
and user content features. International Journal
of Advanced Computer Science and Applications, 13(4), 2022.
Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. Enriching word vectors with subword information. Transactions of the associa-
tion for computational linguistics, 5:135–146, 2017.
Abdeljalil Elouardighi, Mohcine Maghfour, Hafdalla Hammia, and Fatima-zahra Aazi. A machine learning approach for sentiment analysis in the standard or dialectal arabic facebook comments. In 2017 3rd International Conference of Cloud Computing Technologies and Applications (CloudTech), pages 1–8. IEEE, 2017.
Kanchan M Tarwani and Swathi Edem. Survey on recurrent neural network in natural language processing. Int. J. Eng. Trends Technol, 48(6):301–304, 2017.
Gr´egoire Mesnil, Xiaodong He, Li Deng, and Yoshua Bengio. Investigation of recurrent-neuralnetwork architectures and learning methods for spoken language understanding. In Interspeech, pages 3771–3775, 2013.
Peng Zhou, Zhenyu Qi, Suncong Zheng, Jiaming Xu, Hongyun Bao, and Bo Xu. Text classification improved by integrating bidirectional lstm with two-dimensional max pooling. arXiv preprint
arXiv:1611.06639, 2016.
Suad A Alasadi and Wesam S Bhaya. Review of data preprocessing techniques in data mining. Journal of Engineering and Applied Sciences, 12(16):4102–4107, 2017.
Kazem Qazanfari and Abdou Youssef. Word embedding by combining resources and integrating techniques. In 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA), pages 438–443. IEEE, 2019.
Yang Mingqiang, Kpalma Kidiyo, Ronsin Joseph, et al. A survey of shape feature extraction techniques. Pattern recognition, 15(7):43–90, 2008.