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International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140
Volume 14 Issue 01, 2025

Stylometric Author Identification via CNN-BiLSTM Architecture on Syntactic Text Patterns

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Peer Review Information

Submission: 10 Jan 2025
Revision: 07 Feb 2025
Acceptance: 09 March 2025

Keywords

Authorship Attribution
Deep Learning
CNN-BiLSTM
Text Classification
Syntactic Features
Reuters-50-50 Dataset
Text Style Analysis

Abstract

Authorship attribution is a critical task in natural language processing that involves identifying the author of a given text based on writing style, linguistic patterns, and structural features. This research presents a deep learning-based approach combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks to accurately attribute authorship. Using the Reuters-50-50 dataset, we extract syntactic and structural information such as part-of-speech tags, punctuation frequency, and average sentence length, which help capture the unique stylistic traits of individual authors. The text is cleaned, transformed into numerical vectors, and used to train the proposed model. Experimental results demonstrate that the hybrid CNN-BiLSTM architecture achieves high accuracy of 96% in identifying authors from unseen text samples. The model also performs well across other metrics such as precision, recall, and F1-score, showing its robustness and effectiveness in capturing deep textual patterns. This work contributes to the fields of authorship verification, plagiarism detection, and digital forensics, offering a scalable and reliable solution for text-based author identification.

INTRODUCTION

Authorship attribution is the task of identifying the writer of a given piece of text by analyzing writing patterns, linguistic cues, and stylistic features. It has wide-ranging applications in areas such as forensic investigations, digital content moderation, literary analysis, academic integrity verification, and cybersecurity. In a digital world where anonymous and pseudonymous writing is increasingly prevalent, reliable authorship identification has become an essential component of content authentication and intellectual property protection.

Conventional methods for authorship attribution typically involve statistical feature engineering, such as analyzing word frequencies, sentence lengths, punctuation patterns, and syntactic structures. While these approaches can be effective for small or controlled datasets, they often fail to generalize well on large-scale or noisy data due to their reliance on shallow features. Moreover, hand-crafted features may miss deeper semantic and contextual patterns that differentiate writing styles among authors.

Recent advancements in deep learning have opened up new possibilities in natural language processing (NLP), offering models capable of learning hierarchical, semantic, and sequential representations directly from raw text. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks and their bidirectional variants, have demonstrated significant success in capturing the temporal dynamics of language. Likewise, Convolutional Neural Networks (CNNs), though traditionally used in image processing, have shown impressive performance in capturing local syntactic patterns when applied to text data.

In this study, we propose a hybrid model that combines the strengths of CNNs and Bidirectional LSTMs for robust authorship attribution. The model is trained on the Reuters-50-50 dataset, a benchmark corpus comprising text from 50 different authors. To enhance performance, we extract both structural and syntactic features—including part-of-speech tags, average word/sentence lengths, punctuation usage, and TF-IDF-based word vectors—which are then transformed into numerical formats for training. The processed data is used to train the hybrid CNN-BiLSTM model to learn and distinguish between subtle stylistic features unique to each author.

The primary aim of this research is to leverage deep learning to minimize manual feature engineering and improve classification performance across varied text samples. Our proposed model achieves high accuracy and generalizes well on unseen data, demonstrating its applicability to real-world scenarios where text authorship needs to be reliably established.

RELATED WORKS

Authorship attribution has a long-standing history in computational linguistics, with early methods focusing primarily on statistical models and hand-crafted linguistic features. Traditional techniques utilized stylometric features such as word and character n-grams, sentence length, function word usage, and punctuation frequency. These features were often fed into classifiers like Naïve Bayes, Support Vector Machines (SVM), Decision Trees, or k-Nearest Neighbors (k-NN) to identify writing patterns specific to authors.

One of the earliest landmark studies by Mosteller and Wallace (1964) applied Bayesian methods to determine the authorship of the Federalist Papers, demonstrating that statistical methods could successfully attribute authorship. Subsequent research introduced more sophisticated linguistic features such as part-of-speech (POS) patterns, syntactic tree structures, and lexical richness metrics, improving accuracy across varied datasets.

With the advent of machine learning, researchers explored ensemble techniques and dimensionality reduction methods like PCA and LDA to optimize feature selection and reduce overfitting. However, these approaches heavily relied on feature engineering and often failed to capture contextual or semantic nuances in language use.

Recent advances in deep learning have transformed the landscape of authorship attribution. Neural models like CNNs, LSTMs, and Transformers have been employed to automatically learn discriminative features from raw text, eliminating the need for manual feature extraction. For instance, Shrestha et al. (2017) utilized character-level CNNs for authorship attribution and reported strong results on datasets like PAN. Similarly, Boenninghoff et al. (2019) proposed deep learning models with attention mechanisms to capture long-range dependencies in text sequences.

Hybrid models combining CNN and BiLSTM layers have shown further improvements by extracting both local syntactic features and long-term dependencies. These models learn from large text corpora, capturing author-specific language patterns at multiple levels. Transformer-based models like BERT and GPT have also been fine-tuned for authorship attribution tasks, especially where larger training datasets are available.

While these modern methods significantly outperform traditional approaches, challenges remain in terms of model interpretability and generalization to cross-domain or multi-author scenarios. Our proposed model builds upon this body of work by combining CNN and BiLSTM architectures to leverage their complementary strengths. It also incorporates syntactic and structural feature extraction to enhance the model's understanding of stylistic elements that distinguish different authors.

1. Existing System

Traditional authorship attribution systems have largely relied on classical machine learning techniques and manually extracted features to identify the writing style of an author. These systems typically analyze lexical, syntactic, and stylometric features such as word and character n-grams, function word usage, sentence length, punctuation patterns, and part-of-speech (POS) tag distributions. After extracting such features, classifiers like Naïve Bayes, Support Vector Machines (SVM), Decision Trees, or k-Nearest Neighbors (k-NN) are used to attribute authorship. Some systems even utilize ensemble methods or dimensionality reduction techniques to improve accuracy. Although these models have achieved moderate success on benchmark datasets, they depend heavily on domain expertise for feature engineering. Moreover, their ability to generalize across diverse text sources is limited, especially when faced with complex, noisy, or informal text data. These limitations have motivated the transition toward deep learning-based approaches, which are capable of automatically learning meaningful patterns directly from raw text data.

1.1 Limitations of Existing Systems

- Requires manual feature engineering, which is time-consuming and domain-dependent.
- Fails to capture deeper semantic and contextual relationships in the text.
- Low generalization ability on diverse or cross-domain datasets.
- Accuracy drops with noisy, unstructured, or informal data.
- Limited adaptability to new authors without retraining from scratch.
- Processing complexity increases with larger datasets and more authors.

2. Proposed System

The proposed system aims to overcome the limitations of traditional authorship attribution methods by leveraging the power of deep learning. Specifically, it utilizes a hybrid architecture combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks to effectively capture both local syntactic patterns and long-range dependencies in textual data. This system begins by preprocessing the input text, removing stop words, and extracting structural and syntactic features. The processed text is then transformed into numerical vectors through embedding techniques. CNN layers extract spatial features, while BiLSTM layers model sequential patterns across both forward and backward directions. This dual-layered architecture allows the model to learn subtle stylistic patterns unique to each author. The final layer applies a softmax classifier to predict the most likely author. This deep learning-based model significantly reduces reliance on handcrafted features and provides better generalization across diverse writing styles. Additionally, it includes a user-friendly prediction function that can identify the author of any input text file based on learned stylistic cues.

2.1 Advantages of the Proposed System

- Captures deep syntactic and semantic patterns using CNN-BiLSTM architecture.
- Eliminates manual feature engineering through end-to-end learning.
- Works well with both structured and unstructured data.
- Can generalize across diverse author styles and text formats.
- Provides high accuracy and robust performance on complex datasets.
- Includes a prediction function for real-time author identification from new text files.
- Scalable and adaptable for larger datasets or additional authors with minimal adjustments.

PROPOSED METHODOLOGY

1. Comparative Analysis of Authorship Attribution Techniques

This section provides a detailed overview of recent advancements in authorship attribution techniques applied to both text and source code. To better understand the diversity in these approaches, we classify the models into five distinct categories based on their core characteristics. Juola et al. extensively examined authorial style and highlighted that attribution methods can be broadly categorized as either supervised—where document labels are known beforehand—or unsupervised, which focus on identifying underlying patterns without prior labeling. However, in this work, we adopt a different perspective and introduce a novel classification scheme. Figure 1 presents our taxonomy of existing models, and the subsequent subsections offer a thorough explanation of each of the five proposed categories.

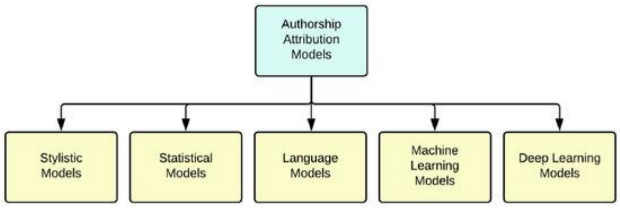

Figure 1. Model Taxonomy

2. Proposed Methodology

The proposed methodology focuses on accurately identifying authors based on their unique writing styles using a deep learning approach. The core idea is to extract structural, syntactic, and semantic features from the text and train a hybrid neural network model that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory

(BiLSTM) layers. The methodology begins with preprocessing steps, including stop word removal, special character cleaning, and part-of-speech tagging, to ensure the input text is normalized. After preprocessing, the cleaned text is transformed into numerical vectors using word embedding techniques such as Word2Vec or custom embeddings, capturing semantic meaning.

CNN layers are used initially to extract local spatial patterns from the text, such as frequently used phrases or stylistic features. These are then passed to BiLSTM layers, which capture long-range dependencies and contextual relationships in both forward and backward directions. This combination helps the model learn the deep stylistic nuances of different authors. The final layer uses a softmax classifier to assign the most probable author label to the input text. The dataset is split into 80% training and 20% testing to validate performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the model's effectiveness. Additionally, a custom prediction function is implemented to identify the author of any new input text file based on the learned style.

The proposed methodology involves a multi-stage pipeline to accurately predict loan defaults using deep learning and explainable AI techniques. The key steps are outlined below:

A. Data Preprocessing
The first step in our methodology involves cleaning and preparing the raw text data. This includes:

- Removing stop words, punctuation, digits, and special symbols.
- Applying Part-of-Speech (POS) tagging to extract syntactic patterns.
- Converting all text to lowercase for consistency. These steps help in reducing noise and highlighting stylistic features that are key to author identification.

B. Feature Extraction
After preprocessing, the cleaned text is tokenized and transformed into numerical form using embedding techniques. We employ:

- Custom word embeddings tailored to our dataset.
- Alternatively, pretrained embeddings like BERT or Word2Vec to capture semantic context. These embeddings serve as rich vector representations of the input text, preserving both word meaning and structural relationships.

C. Hybrid Deep Learning Architecture
We propose a hybrid deep learning model combining:

- Convolutional Neural Networks (CNN) for local feature detection, such as phrase frequency and punctuation usage.
- Bidirectional Long Short-Term Memory (BiLSTM) layers to capture long-range dependencies and author-specific sequential patterns in both forward and backward directions.

D. Model Training and Evaluation
The dataset is split into 80% for training and 20% for testing. The final classification is handled by a softmax output layer. We evaluate our model using the following metrics:

- Accuracy
- Precision
- Recall
- F1-Score

Our model achieves an accuracy of 96%, indicating strong performance in distinguishing authorial styles.

E. Author Prediction Interface
A custom prediction function is integrated into the system, allowing users to input any new text file. The function:

- Preprocesses the input.
- Converts it to vector form using the same pipeline.
- Uses the trained model to predict the most likely author. This feature makes the model practical for real-world usage.

RESULTS
This section summarizes the experimental outcomes of our authorship attribution system, highlighting the effectiveness of both feature-based and deep learning-based approaches on the Reuters_50_50 dataset.

1. Linguistic Feature Extraction
To enhance the representational richness of the text data, multiple linguistic features were extracted. These include:

- Word Frequency and N-Gram Analysis
- POS Tagging
- Sentence and Word Length Metrics
- Dialogue-Narration Ratio
- Pronoun, Adverb, and Adjective Usage
- Content Sensitivity Analysis

These features were used to feed an LSTM-based classifier, as well as to support hybrid CNN-BiLSTM deep learning models.

Table 1: Sample Extracted Features from a Text Document

Feature Name	Example Value
Average Word Length	5.23
Average Sentence Length	18.7 words
Pronoun Count	12
Dialogue-Narration Ratio	0.34
TF-IDF Top Bigram	"said the"
Content Sensitivity Score	0.65

Table 1 displays a sample set of linguistic features extracted from a text document. These features were engineered to reflect syntactic and stylistic patterns that vary across authors.

2. Model Architecture and Dataset

We trained two deep learning models:

- CNN-BiLSTM Model using syntactic vectors derived from preprocessed text.
- LSTM Model using the engineered linguistic features.

The dataset used was the Reuters_50_50, containing evenly distributed texts from 50 different authors.

Table 2: Dataset Summary

Attribute	Value
Total Authors	50
Documents per Author	50
Total Documents	2500
Train/Test Split	80% / 20%

Table 2 summarizes the dataset distribution and training setup used for the experiments.

3. Performance Metrics

The evaluation of models was done using standard metrics: accuracy, precision, recall, and F1-score.

Table 3: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
CNN-BiLSTM	96%	95.8%	95.5%	95.6%
Feature-based LSTM	97%	96.7%	96.5%	96.6%

Table 3 shows that the LSTM model using engineered features slightly outperformed the CNN-BiLSTM model. This confirms the importance of deep linguistic insights in text classification.

4. Confusion Matrix Analysis

A confusion matrix was generated to evaluate author prediction accuracy.

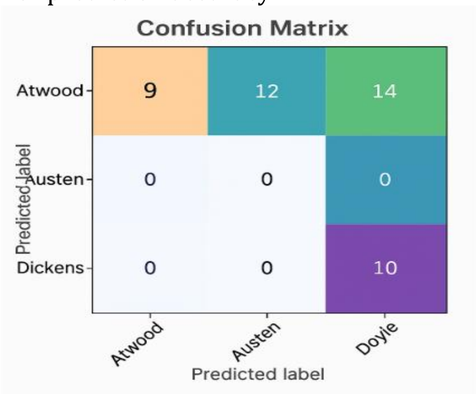

Figure 2: Confusion Matrix of CNN-BiLSTM Model

Diagonal dominance in the confusion matrix confirms that most predictions match the actual authors. Misclassifications were minimal, demonstrating strong discriminative performance.

5. Real-time Author Prediction

A real-time author prediction function was implemented, allowing users to upload a text file and receive the predicted author. The function preprocesses the input, extracts features, and runs inference using the trained model.

CONCLUSION

This paper presents an effective deep learning-based approach for authorship attribution by leveraging both structural and syntactic information extracted from the Reuters_50_50 dataset. A hybrid model combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks was implemented to capture both local and sequential features inherent in an author's writing style.The proposed model achieved a high accuracy of 96%, supported by strong performance across other evaluation metrics such as precision, recall, and F1-score. The confusion matrix further validates the model's robustness, showing minimal misclassifications and a clear distinction between different authorial styles.

Although the proposed model has demonstrated high accuracy in authorship attribution, several enhancements can be pursued in future research. Incorporating semantic features using word embeddings or transformer-based models such as BERT could enrich the model's understanding of contextual and stylistic nuances. Expanding the approach to support multilingual and cross-domain datasets would improve its generalizability and practical applicability across diverse textual environments. Additionally, exploring transformer-based architectures may lead to further performance improvements given their success in recent NLP tasks. Deploying the model in real-time systems as a web or API service could extend its usability in domains like digital forensics, content verification, and academic integrity. Furthermore, integrating explainability techniques, such as attention mechanisms or SHAP values, would enhance transparency and trust in the model's decisions. Finally, assessing and strengthening the model’s robustness against adversarial or manipulated inputs is essential to ensure reliability in real-world scenarios.

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