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Author Identification from Literary Articles with Visual Features: A Case Study with Bangla Documents

Ankita Dhar [1], Himadri Mukherjee [2], Shibaprasad Sen [3], Md Obaidullah Sk [4], Amitabha Biswas [2], Teresa Gonçalves [5,6] and Kaushik Roy [2,*]

[1] Department of Computational Science, Brainware University, Kolkata 700125, India
[2] Department of Computer Science, West Bengal State University, Kolkata 700126, India
[3] Techno Main Saltlake, Kolkata 700091, India
[4] Department of Computer Science and Engineering, Aliah University, Kolkata 700156, India
[5] Department of Computer Science, University of Évora, 7000-671 Évora, Portugal
[6] ALGORITMI Research Center, Vista Lab, University of Évora, 7000-671 Évora, Portugal
* Correspondence: kaushik.mrg@gmail.com

Abstract: Author identification is an important aspect of literary analysis, studied in natural language processing (NLP). It aids identify the most probable author of articles, news texts or social media comments and tweets, for example. It can be applied to other domains such as criminal and civil cases, cybersecurity, forensics, identification of plagiarizer, and many more. An automated system in this context can thus be very beneficial for society. In this paper, we propose a convolutional neural network (CNN)-based author identification system from literary articles. This system uses visual features along with a five-layer convolutional neural network for the identification of authors. The prime motivation behind this approach was the feasibility to identify distinct writing styles through a visualization of the writing patterns. Experiments were performed on 1200 articles from 50 authors achieving a maximum accuracy of 93.58%. Furthermore, to see how the system performed on different volumes of data, the experiments were performed on partitions of the dataset. The system outperformed standard handcrafted feature-based techniques as well as established works on publicly available datasets.

Keywords: author identification; statistical-based features; image-based features; deep learning; CNN

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1. Introduction

The task of an author identification system is to recognize the respective author of an article from a set of authors. From the machine learning perspective, this task can be viewed as a multiclass text categorization problem where the classes identify the authors. Identifying authors from texts or paragraphs of poems, novels, essays, and stories can prove significant for a literary analysis. The proposed system can be beneficial to students for retrieving information regarding a major subject, e.g., literature. Furthermore, in some scenarios, various literary articles are encountered without author's identification. This system can help users identify the respective author of the article in question. The style of writing depends on an author's linguistic choice reflecting in one's piece of art. One of the current and emanating fashion in author identification tasks is to extract the features from the piece of art computationally rather than extracting them manually, demanding the development of an automatic author identification system. Author identification can also be used in different natural language processing fields that involve criminal and civil law, bibliometrics, plagiarism detection, cybersecurity, forensics, and many more.

However, this is not a trivial task because of the occurrence of similar words and phrases within texts. At times, certain works of literature are inspired by works from different writers, leading to interclass similarities. The study of stylometry and author identification or profiling started back in the 19th century when Mendenhall [1] characterized the writing pattern of different authors using the frequency distribution of terms of varying lengths. In the early 20th century, various statistical features were studied involving metrics for stylometry such as Zipf's distribution and Yule's K measure. Later, Mosteller and Wallace [2] worked with Bayesian statistical measures where the frequencies of a small set of function words were analyzed as the stylistic features of the text. Many other different measures have been explored to extract stylistic features from the text for author identification tasks. Recently, deep learning has been studied in various natural language processing tasks, providing better performance when compared to previous state-of-the-art approaches.

In this paper, we propose a system that uses visual features along with a five-layer convolutional neural network for the identification of authors through the recognition of distinct writing patterns. Statistical as well as internal features were extracted and represented by three different types of charts (line, imagesc, and pie) that were then fed to a convolutional neural network. The experiments were done on 1200 literary articles written by 50 different authors from different generations, obtaining a maximum accuracy of 93.58%. Furthermore, the system performance was tested with a varied number of authors (from 5 to 50) to see how the features work on an incremental number of authors (and dataset sizes), as well as with a different number of features to perceive their discrete aspects on the studied datasets.

The work was performed on the Bangla language as it is the sixth most spoken language with approximately 265 million users in the world [3]. Since no such corpus was available in Bangla, we built one consisting of 1200 articles written by 50 different authors from different generations, totaling 323,780,594 tokens. The proposed system uses image-based features along with a lightweight CNN. This helps to visualize the writing patterns of an author (by observing the charts) rather than observing the relevant keywords by reading the articles.

The organization of the paper is the following: Section 2 presents a brief literature study on the existing research in this domain; Section 3 discusses the proposed methodology and Section 4 presents the experimental setup and discusses the results obtained. Finally, Section 5 concludes the paper with some future directions.

2. Related Work

We provide a brief survey considering works carried out in different languages. Qian et al. [4] explored various deep learning architectures on different corpora. Their experimental results showed that the article-level GRU obtained a maximum accuracy of 69.1% and 89.2% on the C50 and Gutenberg corpora, respectively. Mohsen et al. [5] used a deep learning architecture to extract features from articles based on different character-based n-gram approaches. They also investigated the application of various feature extraction and selection approaches using a stacked denoising autoencoder and support vector machines to build the classifier.

Zhang et al. [6] proposed a semantic relationship-based unsupervised method for identifying the writing pattern of different authors using principal component analysis and linear discriminant analysis based on expression, term relevancy, and nonsubject stylistic term from different articles. Benzebouchi et al. [7] used the word2vec word embeddings model, which provides semantic relationships between words, along with the multilayer perceptron (MLP) classification algorithm. The experimental results showed an accuracy of 95.83% on the PAN 2012 dataset [8], indicating a better performance of the system when compared to other standard approaches.

Anwar et al. [9] used the LDA model with n-grams and cosine similarity for identifying authors in English and Urdu documents. They obtained overall accuracies of 84.52% and 93.17% on the PAN 2012 dataset [8] and Urdu news articles. Rexha et al. [10] conducted two experiments, firstly comparing the decisions using content and stylometric features and secondly, describing the process and the features on which their judgment was based.

Pandian et al. [11] trained a decision tree (J48 learning algorithm) using text-based features for identifying different authors of poems. Nirkhi et al. [12] worked with word and character unigram features and a support vector machine (SVM) classifier on the C50 dataset and achieved 88% accuracy. López-Monroy et al. [13] also used an SVM along with the bag-of-terms model, obtaining 80.80% accuracy on the C50 dataset for the author identification task.

Bevendorff et al. [14] provided a brief discussion on the results of the four shared tasks arranged at the PAN 2020 [15] lab on digital text forensics and stylometry. This involved author profiling, cross-domain author verification, celebrity profiling, and style change detection. The aim was to advance the existing approaches and evaluate them on new standard datasets. Sarwar and Hassan [16] worked with stylometric features to overcome the limitations of having only n-gram features for Urdu texts; their experimental results showed an accuracy of 94.03%, indicating a discriminative power of the stylometric features used.

Chakraborty and Choudhury [17] tested three different graph-based algorithms and, for each algorithm, the graphs were clustered, and the weights were assigned based on the graph traversal method. Experiments were done using articles from six authors obtaining a maximum accuracy of 94.98%. Using SMO along with the J48 algorithm, Digamberrao and Prasad [18] implemented two techniques that used lexical and stylistic feature extraction processes for identifying authors from 15 philosophical articles written in Marathi by five authors, achieving an accuracy of 80%.

Rakshit et al. [19] used semantic-based and stylistic-based features and the support vector machine algorithm for identifying poems from four genres and achieved an accuracy of 92.3%. Anisuzzaman and Salam [20] proposed a hybrid model by combining word n-grams with the naïve Bayes (NB) algorithm showing an encouraging accuracy of 95%.

A brief analysis of the literature study is provided in the following Table 1.

Table 1. The brief analysis of the literature study.

Reference	Approach	Accuracy (%)
Qian et al. [4]	Deep learning	89.20
Mohsen et al. [5]	Deep learning	95.12
Zhang et al. [6]	Semantic relationship	95.30
Benzebouchi et al. [7]	Word embeddings and MLP	95.83
Anwar et al. [9]	LDA model with n-grams and cosine similarity	93.17
Rexha et al. [10]	Content and stylometric features	72.00 Confidence
Nirkhi et al. [12]	Unigram and SVM	88.00
López-Monroy et al. [13]	Bag-of-words model with SVM	80.80
Sarwar and Hassan [16]	Stylometric features	94.03
Chakraborty and Choudhury [17]	Graph-based algorithm	94.98
Digamberrao and Prasad [18]	SMO with J48 algorithm	80.00
Rakshit et al. [19]	Stylistic feature and SVM	92.30
Anisuzzaman and Salam [20]	n-gram and NB	95.00

The literature study reveals that various researchers have paid interest to author identification tasks. However, they have mainly focused on the English language [21–25]. Some works focus on other languages as well, such as Arabic [22,26], Dutch [27–29], Greek [30,31], and Portuguese [32,33]. Nonetheless, very few works have been done on Indian languages, especially in Bangla; therefore, there is a pressing need for the development of an automatic author identification system in Bangla. Mostly, researchers have used syntactic, semantic, and stylistic-based features but have not explored various other aspects of the Bangla literary articles from different authors having similar writing styles. Thus, this work uses visual features obtained from the text-based as well as statistical-based features that are fed to a CNN for identifying the author of an article.

3. Proposed Methodology

The automatic author identification approach suggested in this paper used image-based features to categorize writers according to their writing style. Line, picture, and pie charts were used to represent statistical and text-based information, which was then input into a convolutional neural network. A maximum accuracy of 93.58% was reached on an experiment conducted on 1200 articles written by 50 authors of various generations. Additionally, we included a study on a growing number of authors to examine how the features worked on various datasets to perceive the discrete elements of the suggested features on the aforementioned datasets. Figure 1 uses a pictorial representation to explain the process.

In the present work, a database was prepared that comprised 1200 articles from 50 authors which were preprocessed prior to further processing. Here, tokenization and stopword removal were considered for the preprocessing phase as there was no publicly available POS tagger and stemmer/lemmatizer for Bangla, which could be used in our experiment. After receiving the preprocessed data, statistical-based and text-based features were extracted and fed to CNN architecture to identify the authors of a respective article. Furthermore, the results were compared with other supervised machine learning algorithms to see the efficiency of the proposed work.

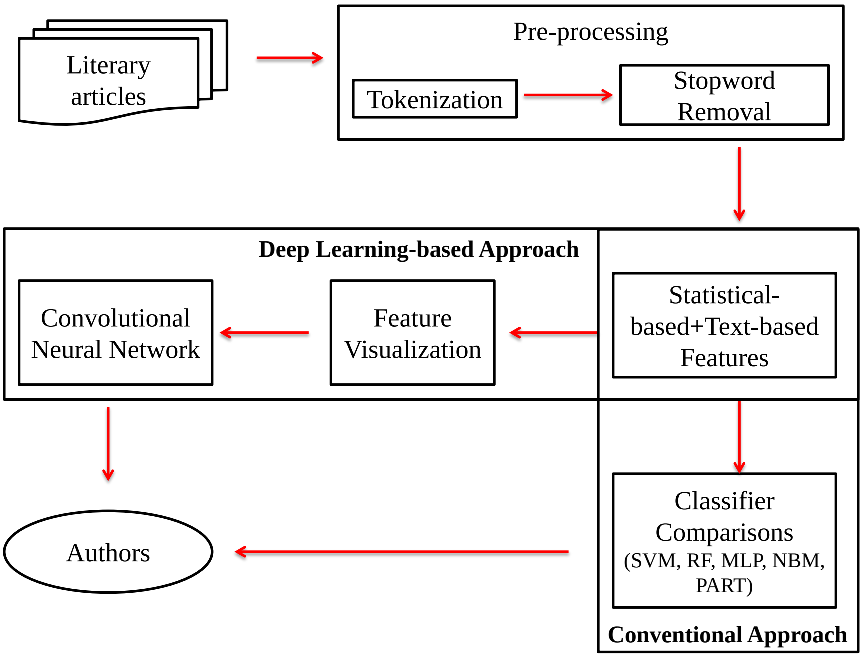
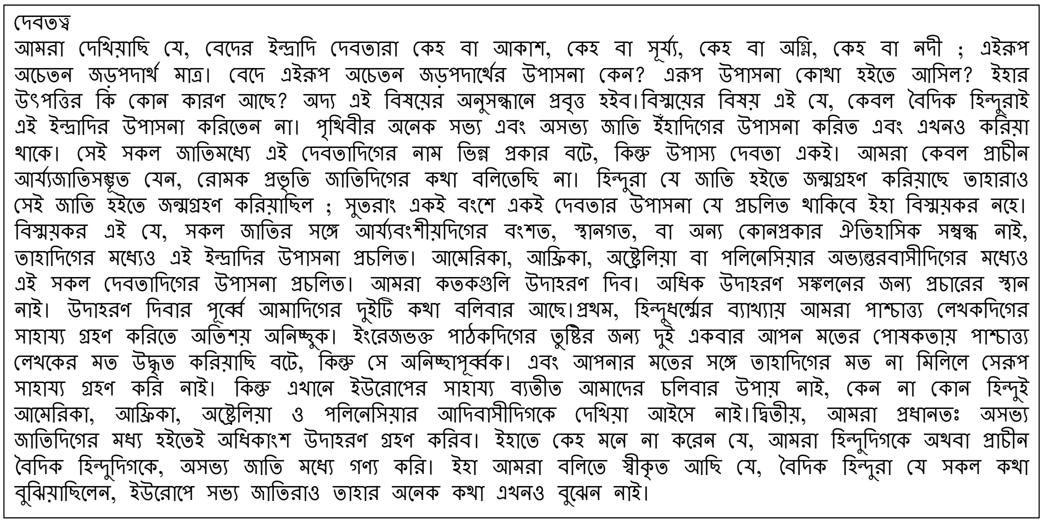

Literary articles
Pre-processing
Tokenization
Stopword Removal
Deep Learning-based Approach
Convolutional Neural Network
Feature Visualization
Statistical-based+Text-based Features
Classifier Comparisons (SVM, RF, MLP, NBM, PART)
Conventional Approach
Authors

Figure 1. The methodology of the proposed work.

3.1. Data Collection

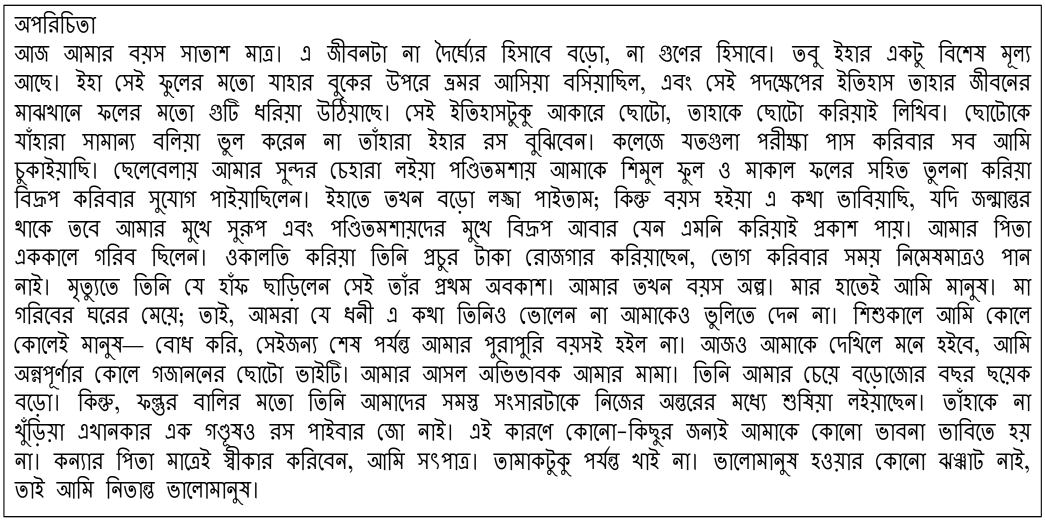
The literature study highlighted that there were no publicly available author identification datasets for the Bangla language. Therefore, for the present experiment, a corpus was prepared consisting of 1200 articles from 50 authors. There were difficulties during the development of the corpus in Bengali, as there were limited resources available on the internet [3]. The number of articles per author varied from 10 to 22. The developed corpus comprised articles from different literature types involving novels, essays, and big stories with similar writing styles obtained from www.ebanglalibrary.com (accessed on 17 January 2022). The dataset was digitized so that it could be used for developing automatic author identification systems. The maximum and minimum number of words present in a sentence was 16 and 9, respectively. The standard deviation of the dataset consisting of texts per author was 4.65. A sample text of four articles from four different authors is presented in Figures 2–5 to give a glimpse of the data used in the experiments.



দেবতত্ব

আমরা দেখিয়াছি যে, বেদের ইন্দ্রাদি দেবতারা কেহ বা আকাশ, কেহ বা সূর্য্য, কেহ বা অগ্নি, কেহ বা নদী ; এইরূপ অচেতন জড়পদার্থ মাত্র। বেদে এইরূপ অচেতন জড়পদার্থের উপাসনা কেন? এরূপ উপাসনা কোথা হইতে আসিল? ইহার উৎপত্তির কি কোন কারণ আছে? অদ্য এই বিষয়ের অনুসন্ধানে প্রবৃত্ত হইব।বিস্ময়ের বিষয় এই যে, কেবল বৈদিক হিন্দুরাই এই ইন্দ্রাদির উপাসনা করিতেন না। পৃথিবীর অনেক সভ্য এবং অসভ্য জাতি ইঁহাদিগের উপাসনা করিত এবং এখনও করিয়া থাকে। সেই সকল জাতিমধ্যে এই দেবতাদিগের নাম ভিন্ন প্রকার বটে, কিন্তু উপাস্য দেবতা একই। আমরা কেবল প্রাচীন আর্য্যজাতিসম্ভূত যেন, রোমক প্রভৃতি জাতিদিগের কথা বলিতেছি না। হিন্দুরা যে জাতি হইতে জন্মগ্রহণ করিয়াছে তাহারাও সেই জাতি হইতে জন্মগ্রহণ করিয়াছিল ; সুতরাং একই বংশে একই দেবতার উপাসনা যে প্রচলিত থাকিবে ইহা বিস্ময়কর নহে। বিস্ময়কর এই যে, সকল জাতির সঙ্গে আর্য্যবংশীয়দিগের বংশত, স্থানগত, বা অন্য কোনপ্রকার ঐতিহাসিক সম্বন্ধ নাই, তাহাদিগের মধ্যেও এই ইন্দ্রাদির উপাসনা প্রচলিত। আমেরিকা, আফ্রিকা, অষ্ট্রেলিয়া বা পলিনেসিয়ার অভ্যন্তরবাসীদিগের মধ্যেও এই সকল দেবতাদিগের উপাসনা প্রচলিত। আমরা কতকগুলি উদাহরণ দিব। অধিক উদাহরণ সঙ্কলনের জন্য প্রচারের স্থান নাই। উদাহরণ দিবার পূর্ব্বে আমাদিগের দুইটি কথা বলিবার আছে।প্রথম, হিন্দুধর্ম্মের ব্যাখ্যায় আমরা পাশ্চাত্ত্য লেখকদিগের সাহায্য গ্রহণ করিতে অতিশয় অনিচ্ছুক। ইংরেজভক্ত পাঠকদিগের তুষ্টির জন্য দুই একবার আপন মতের পোষকতায় পাশ্চাত্ত্য লেখকের মত উদ্ধৃত করিয়াছি বটে, কিন্তু সে অনিচ্ছাপূর্ব্বক। এবং আপনার মতের সঙ্গে তাহাদিগের মত না মিলিলে সেরূপ সাহায্য গ্রহণ করি নাই। কিন্তু এখানে ইউরোপের সাহায্য ব্যতীত আমাদের চলিবার উপায় নাই, কেন না কোন হিন্দুই আমেরিকা, আফ্রিকা, অষ্ট্রেলিয়া ও পলিনেসিয়ার আদিবাসীদিগকে দেখিয়া আইসে নাই।দ্বিতীয়, আমরা প্রধানতঃ অসভ্য জাতিদিগের মধ্য হইতেই অধিকাংশ উদাহরণ গ্রহণ করিব। ইহাতে কেহ মনে না করেন যে, আমরা হিন্দুদিগকে অথবা প্রাচীন বৈদিক হিন্দুদিগকে, অসভ্য জাতি মধ্যে গণ্য করি। ইহা আমরা বলিতে স্বীকৃত আছি যে, বৈদিক হিন্দুরা যে সকল কথা বুঝিয়াছিলেন, ইউরোপে সভ্য জাতিরাও তাহার অনেক কথা এখনও বুঝেন নাই।

Figure 2. The sample text written by Bankim Chandra Chattopadhyay [3].



অপরিচিতা

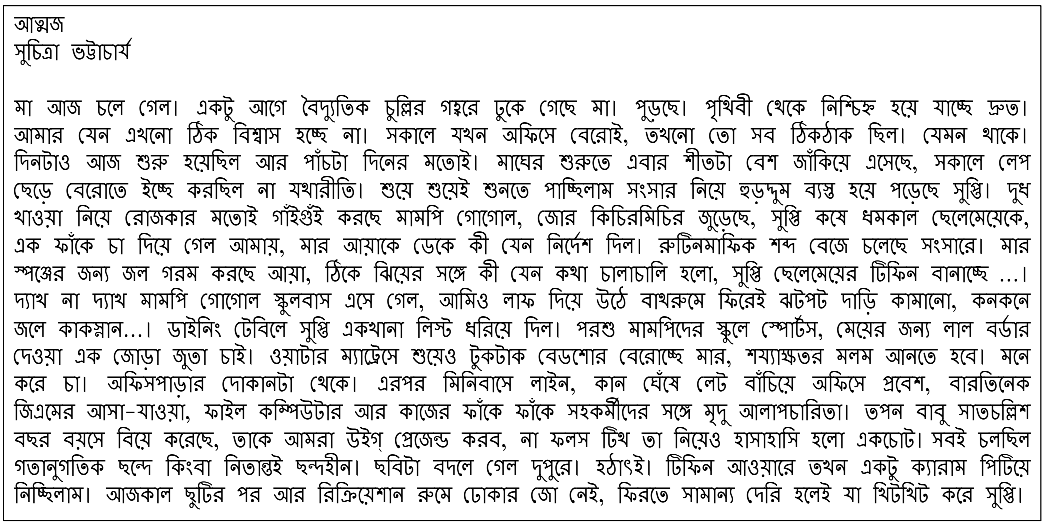
আজ আমার বয়স সাতাশ মাত্র। এ জীবনটা না দৈর্ঘ্যের হিসাবে বড়ো, না গুণের হিসাবে। তবু ইহার একটু বিশেষ মূল্য আছে। ইহা সেই ফুলের মতো যাহার বুকের উপরে ভ্রমর আসিয়া বসিয়াছিল, এবং সেই পদক্ষেপের ইতিহাস তাহার জীবনের মাঝখানে ফলের মতো গুটি ধরিয়া উঠিয়াছে। সেই ইতিহাসটুকু আকারে ছোটো, তাহাকে ছোটো করিয়াই লিখিব। ছোটোকে যাঁহারা সামান্য বলিয়া ভুল করেন না তাঁহারা ইহার রস বুঝিবেন। কলেজে যতগুলা পরীক্ষা পাস করিবার সব আমি চুকাইয়াছি। ছেলেবেলায় আমার সুন্দর চেহারা লইয়া পণ্ডিতমশায় আমাকে শিমুল ফুল ও মাকাল ফলের সহিত তুলনা করিয়া বিদ্রূপ করিবার সুযোগ পাইয়াছিলেন। ইহাতে তখন বড়ো লজ্জা পাইতাম; কিন্তু বয়স হইয়া এ কথা ভাবিয়াছি, যদি জন্মান্তর থাকে তবে আমার মুখে সুরূপ এবং পণ্ডিতমশায়দের মুখে বিদ্রূপ আবার যেন এমনি করিয়াই প্রকাশ পায়। আমার পিতা এককালে গরিব ছিলেন। ওকালতি করিয়া তিনি প্রচুর টাকা রোজগার করিয়াছেন, ভোগ করিবার সময় নিমেষমাত্রও পান নাই। মৃত্যুতে তিনি যে হাঁফ ছাড়িলেন সেই তাঁর প্রথম অবকাশ। আমার তখন বয়স অল্প। মার হাতেই আমি মানুষ। মা গরিবের ঘরের মেয়ে; তাই, আমরা যে ধনী এ কথা তিনিও ভোলেন না আমাকেও ভুলিতে দেন না। শিশুকালে আমি কোলে কোলেই মানুষ— বোধ করি, সেইজন্য শেষ পর্যন্ত আমার পুরাপুরি বয়সই হইল না। আজও আমাকে দেখিলে মনে হইবে, আমি অন্নপূর্ণার কোলে গজাননের ছোটো ভাইটি। আমার আসল অভিভাবক আমার মামা। তিনি আমার চেয়ে বড়োজোর বছর ছয়েক বড়ো। কিন্তু, ফল্গুর বালির মতো তিনি আমাদের সমস্ত সংসারটাকে নিজের অন্তরের মধ্যে শুষিয়া লইয়াছেন। তাঁহাকে না খুঁড়িয়া এখানকার এক গণ্ডূষও রস পাইবার জো নাই। এই কারণে কোনো-কিছুর জন্যই আমাকে কোনো ভাবনা ভাবিতে হয় না। কন্যার পিতা মাত্রেই স্বীকার করিবেন, আমি সৎপাত্র। তামাকটুকু পর্যন্ত খাই না। ভালোমানুষ হওয়ার কোনো ঝঞ্ঝাট নাই, তাই আমি নিতান্ত ভালোমানুষ।

Figure 3. The sample text written by Rabindranath Tagore [3].

An experimentation was also carried out with a varied number of authors (5, 10, 15, 20, 25, 30, 35, 40, and 45) to perceive the characteristics of the features on incremental corpora sizes. The partition was done keeping in mind the scenario of having articles written by different authors of different ages with similar writing patterns so that the comparison was fair. The resulting partitioned corpora, illustrating the number of articles, are provided in Table 2.

3.2. Preprocessing

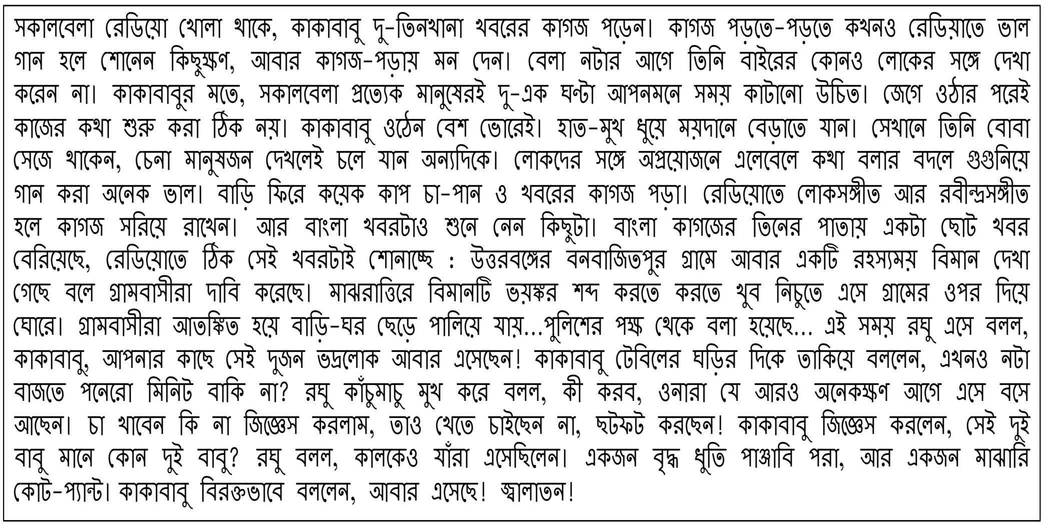
Before the extraction of the features, articles were preprocessed. The texts were tokenized using a space delimiter and a total of 323,780,594 tokens were obtained. Stopwords are tokens not relevant for the identification task; in this experiment, 355 Bangla stopwords were considered, following the list specified in [34]. After stopword removal, the corpus had a total of 267,632,425 tokens, with 200,829 unique ones. The statistical analysis of the data after preprocessing is provided in Table 3.



আত্মজ
সুচিত্রা ভট্টাচার্য

মা আজ চলে গেল। একটু আগে বৈদ্যুতিক চুল্লির গহ্বরে ঢুকে গেছে মা। পুড়ছে। পৃথিবী থেকে নিশ্চিহ্ন হয়ে যাচ্ছে দ্রুত। আমার যেন এখনো ঠিক বিশ্বাস হচ্ছে না। সকালে যখন অফিসে বেরোই, তখনো তো সব ঠিকঠাক ছিল। যেমন থাকে। দিনটাও আজ শুরু হয়েছিল আর পাঁচটা দিনের মতোই। মাঘের শুরুতে এবার শীতটা বেশ জাঁকিয়ে এসেছে, সকালে লেপ ছেড়ে বেরোতে ইচ্ছে করছিল না যথারীতি। শুয়ে শুয়েই শুনতে পাচ্ছিলাম সংসার নিয়ে হুড়দ্দুম ব্যস্ত হয়ে পড়েছে সুপ্তি। দুধ খাওয়া নিয়ে রোজকার মতোই গাঁইগুঁই করছে মামপি গোগোল, জোর কিচিরমিচির জুড়েছে, সুপ্তি কষে ধমকাল ছেলেমেয়েকে, এক ফাঁকে চা দিয়ে গেল আমায়, মার আয়াকে ডেকে কী যেন নির্দেশ দিল। রুটিনমাফিক শব্দ বেজে চলেছে সংসারে। মার স্পঞ্জের জন্য জল গরম করছে আয়া, ঠিকে ঝিয়ের সঙ্গে কী যেন কথা চালাচালি হলো, সুপ্তি ছেলেমেয়ের টিফিন বানাচ্ছে ...। দ্যাখ না দ্যাখ মামপি গোগোল স্কুলবাস এসে গেল, আমিও লাফ দিয়ে উঠে বাথরুমে ফিরেই ঝটপট দাড়ি কামানো, কনকনে জলে কাকস্নান...। ডাইনিং টেবিলে সুপ্তি একখানা লিস্ট ধরিয়ে দিল। পরশু মামপিদের স্কুলে স্পোর্টস, মেয়ের জন্য লাল বর্ডার দেওয়া এক জোড়া জুতা চাই। ওয়াটার ম্যাট্রেসে শুয়েও টুকটাক বেডশোর বেরোচ্ছে মার, শয্যাক্ষতর মলম আনতে হবে। মনে করে চা। অফিসপাড়ার দোকানটা থেকে। এরপর মিনিবাসে লাইন, কান ঘেঁষে লেট বাঁচিয়ে অফিসে প্রবেশ, বারতিনেক জিএমের আসা-যাওয়া, ফাইল কম্পিউটার আর কাজের ফাঁকে ফাঁকে সহকর্মীদের সঙ্গে মৃদু আলাপচারিতা। তপন বাবু সাতচল্লিশ বছর বয়সে বিয়ে করেছে, তাকে আমরা উইগ্ প্রেজেন্ড করব, না ফলস টিথ তা নিয়েও হাসাহাসি হলো একচোট। সবই চলছিল গতানুগতিক ছন্দে কিংবা নিতান্তই ছন্দহীন। ছবিটা বদলে গেল দুপুরে। হঠাৎই। টিফিন আওয়ারে তখন একটু ক্যারাম পিটিয়ে নিচ্ছিলাম। আজকাল ছুটির পর আর রিক্রিয়েশান রুমে ঢোকার জো নেই, ফিরতে সামান্য দেরি হলেই যা খিটখিট করে সুপ্তি।

Figure 4. The sample text written by Suchitra Bhattacharya [3].



সকালবেলা রেডিয়ো খোলা থাকে, কাকাবাবু দু-তিনখানা খবরের কাগজ পড়েন। কাগজ পড়তে-পড়তে কখনও রেডিয়াতে ভাল গান হলে শোনেন কিছুক্ষণ, আবার কাগজ-পড়ায় মন দেন। বেলা নটার আগে তিনি বাইরের কোনও লোকের সঙ্গে দেখা করেন না। কাকাবাবুর মতে, সকালবেলা প্রত্যেক মানুষেরই দু-এক ঘন্টা আপনমনে সময় কাটানো উচিত। জেগে ওঠার পরেই কাজের কথা শুরু করা ঠিক নয়। কাকাবাবু ওঠেন বেশ ভোরেই। হাত-মুখ ধুয়ে ময়দানে বেড়াতে যান। সেখানে তিনি বোবা সেজে থাকেন, চেনা মানুষজন দেখলেই চলে যান অন্যদিকে। লোকদের সঙ্গে অপ্রয়োজনে এলেবেলে কথা বলার বদলে গুগুনিয়ে গান করা অনেক ভাল। বাড়ি ফিরে কয়েক কাপ চা-পান ও খবরের কাগজ পড়া। রেডিয়োতে লোকসঙ্গীত আর রবীন্দ্রসঙ্গীত হলে কাগজ সরিয়ে রাখেন। আর বাংলা খবরটাও শুনে নেন কিছুটা। বাংলা কাগজের তিনের পাতায় একটা ছোট খবর বেরিয়েছে, রেডিয়োতে ঠিক সেই খবরটাই শোনাচ্ছে : উত্তরবঙ্গের বনবাজিতপুর গ্রামে আবার একটি রহস্যময় বিমান দেখা গেছে বলে গ্রামবাসীরা দাবি করেছে। মাঝরাত্তিরে বিমানটি ভয়ঙ্কর শব্দ করতে করতে খুব নিচুতে এসে গ্রামের ওপর দিয়ে ঘোরে। গ্রামবাসীরা আতঙ্কিত হয়ে বাড়ি-ঘর ছেড়ে পালিয়ে যায়...পুলিশের পক্ষ থেকে বলা হয়েছে... এই সময় রঘু এসে বলল, কাকাবাবু, আপনার কাছে সেই দুজন ভদ্রলোক আবার এসেছেন! কাকাবাবু টেবিলের ঘড়ির দিকে তাকিয়ে বললেন, এখনও নটা বাজতে পনেরো মিনিট বাকি না? রঘু কাঁচুমাচু মুখ করে বলল, কী করব, ওনারা যে আরও অনেকক্ষণ আগে এসে বসে আছেন। চা খাবেন কি না জিজ্ঞেস করলাম, তাও খেতে চাইছেন না, ছটফট করছেন! কাকাবাবু জিজ্ঞেস করলেন, সেই দুই বাবু মানে কোন দুই বাবু? রঘু বলল, কালকেও যাঁরা এসেছিলেন। একজন বৃদ্ধ ধুতি পাঞ্জাবি পরা, আর একজন মাঝারি কোট-প্যান্ট। কাকাবাবু বিরক্তভাবে বললেন, আবার এসেছে! জ্বালাতন!

Figure 5. The sample text written by Sunil Gangopadhyay [3].

Table 2. The partitioned dataset illustrating the number of articles for each set.

No. of Authors	No. of Articles
5	55
10	160
15	273
20	368
25	468
30	572
35	753
40	905
45	1055
50	1200

Table 3. The statistical analysis of the data after preprocessing.

Analysis per Document	Number of Words
Maximum	3753
Minimum	462
Average	2882

3.3. Feature Extraction

Two different types of characteristics, statistical-based and text-based, were extracted. By giving the tokens weights, the statistically based features took into account the structural relationships from the articles. Here, a variety of statistical measures were used, including the frequency of tokens, the likelihood that an article belonged to a particular author, the similarity between distinct articles and writers, as well as the mean, average, and standard deviation. Text-based features, in contrast, only took into account the lexical information from the articles; they estimated the common and unique vocabulary lists used by various authors in their articles, as well as the combination of characters (simple, compound and complex terms) they used when writing, along with the different n-gram (adjacent order of x terms from a given text) and dictionary-based features.

3.3.1. Statistical-Based Features

The proposed statistical-based features involved various metrics, as discussed below. Let Ar_d represent the articles in the database (d) and Ar_q the article in question (q). The statistical-based features were obtained using Equations (1)–(15), where a_{author} and T_{artl} represent the total number of authors and articles in the dataset, respectively. This study not only estimated the statistical-based features from the articles but also measured the probability of belonging of an article as well.

$Word_{occ_{article}}$: the presence of a token in the article in question

$$Word_{occ_{article}} = t_i | t_i \in Tw_{Ar_q}. \tag{1}$$

$Word_{occ_{articles}}$: the presence of a token in all the articles in the dataset

$$Word_{occ_{articles}} = \frac{Occ(Ar_q, T_{artl})}{Tw_{Ar_q}}. \tag{2}$$

$$Occ(Ar_q, T_{artl}) = t_i | t_i \in \sum_{(Ar_q, Ar_d)}. \tag{3}$$

$Article_{occ}$: counts the presence of a token in a particular category/domain in the entire dataset

$$Article_{occ} = Word_{occ_{article}} \in (a_{author}). \tag{4}$$

$Article_{occ_{prob}}$: the probability of belonging of an article to a specific author

$$Article_{occ_{prob}} = \frac{Occ1(Ar_q, a_{author})}{a_{author}}. \tag{5}$$

$$Occ1(Ar_q, a_{author}) = n_{Ar_q} \in (Ar_q, a_{author}). \tag{6}$$

$Article_{sim}$: counts the similarity of an article to the writing patterns of the associated authors in the dataset

$$Article_{sim} = \frac{sim(Ar_q, T_{artl})}{T_{artl}}. \tag{7}$$

$$sim(Ar_q, T_{artl}) = n_{artl} | n_{artl} \in (Ar_q, T_{artl}). \tag{8}$$

$Author_{sim}$: counts the similarity of the articles among different authors. There may be some similarities in the writing pattern of two or more authors whose information will help the model identify the authors of a particular article.

$$Author_{sim} = \sum_{k=1}^{a_{author}} \frac{sim(Ar_q, T_{artl})}{T_{artl}}. \tag{9}$$

$Total_{sim}$: counts the similarity of an article in question in the entire dataset

$$Total_{sim} = 1/(e^{Word_{occ_{articles}} + Article_{sim} + Author_{sim}}). \tag{10}$$

$Area_{ovrlp}$: counts the overlapping of the content of an article with all the articles in the entire dataset

$$Area_{ovrlp} = \sum_{ovrlp(Tot_t)\in(Ar_q, T_{artl})} . \tag{11}$$

$Article_{ovrlp}$: counts the number of articles overlapped for a specific author in the dataset

$$Article_{ovrlp} = \sum_{ovrlp(Tot_{trtl})\in(a_{author})} . \tag{12}$$

$Mean$: mean of all the articles present in the dataset

$$Mean = \frac{\sum_{i=1}^{i=T_{artl}} Total_{sim_i})}{T_{artl}}. \tag{13}$$

SD: standard deviation of all the articles in the total dataset

$$SD = \sqrt{\frac{\sum_{i=1}^{i=T_{artl}} Total_{sim_i} - Mean)}{T_{artl}}}. \tag{14}$$

Avg_{dev}: deviation of the probability of belongings of a target text with the mean

$$Avg_{dev} = SD - Total_{sim}. \tag{15}$$

3.3.2. Text-Based Features

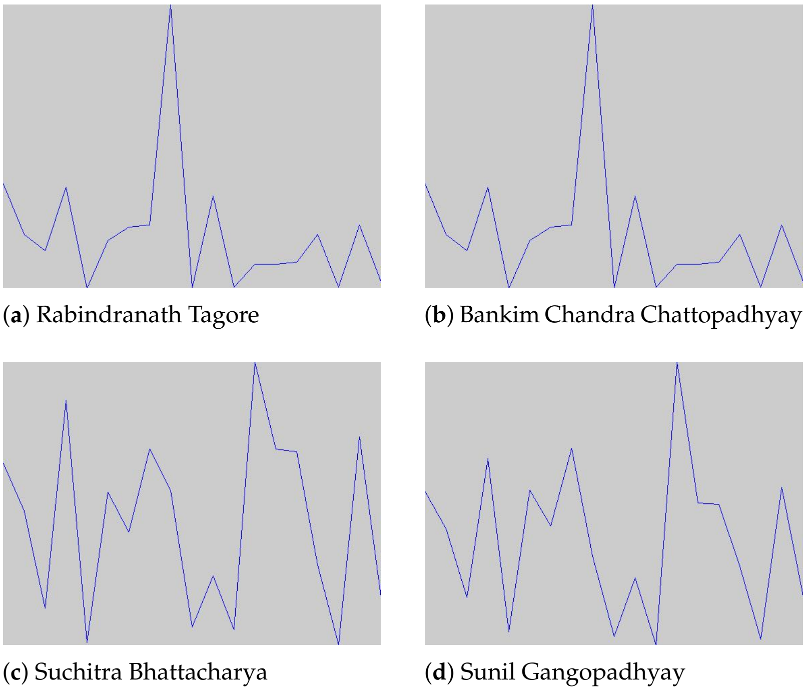
Some text-based features were also proposed to be included as discriminants, such as the common vocabulary set, the unique vocabulary set, a combination of characters, n-grams (n being 2, 3, and 4), and dictionary-based features. Features were extracted on the total dataset as well as on the datasets containing articles with a varied number of authors as discussed in Section 3.1. The combination of characters and dictionary-based features was computed using the list provided in https://github.com/MinhasKamal/BengaliDictionary (accessed on 14 May 2022).

3.3.3. Feature Visualization

On different occasions, it becomes easy to discriminate articles by entirely gazing at the pattern of how they are woven, rather than just reading the articles by observing the relevant keywords. This motivated us to use an image-based feature extraction approach for the identification of authors. The features were visualized by representing them in a 2D plane. Three types of charts, namely line, imagesc, and pie charts, were used for the same feature. The x-axis values for line and imagesc charts represented the 17 features considered in the experiment. Similarly, for a pie chart, each area represented each feature being used here. The y-axis for each chart represented the feature values obtained for each feature.

The imagesc(C) rendered the information in array C as an image that made use of the entire color palette in the colormap. Each C element identified the color for a single picture pixel. An x-by-y grid of pixels, where x represents the number of rows and y represents the number of columns in C, made up the final image. The centers of the relevant pixels were determined by the row and column indexes of the elements. Similarly, the pie chart followed a color scheme palette that has 3 colors: Burnt Sienna (#EC6B56), Crayola's Maize (#FFC154) and Keppel (#47B39C). Here, we considered the "hsv" theme. According to the selected palette, the color combination built up. However, for the line chart, a default color was chosen for the line.

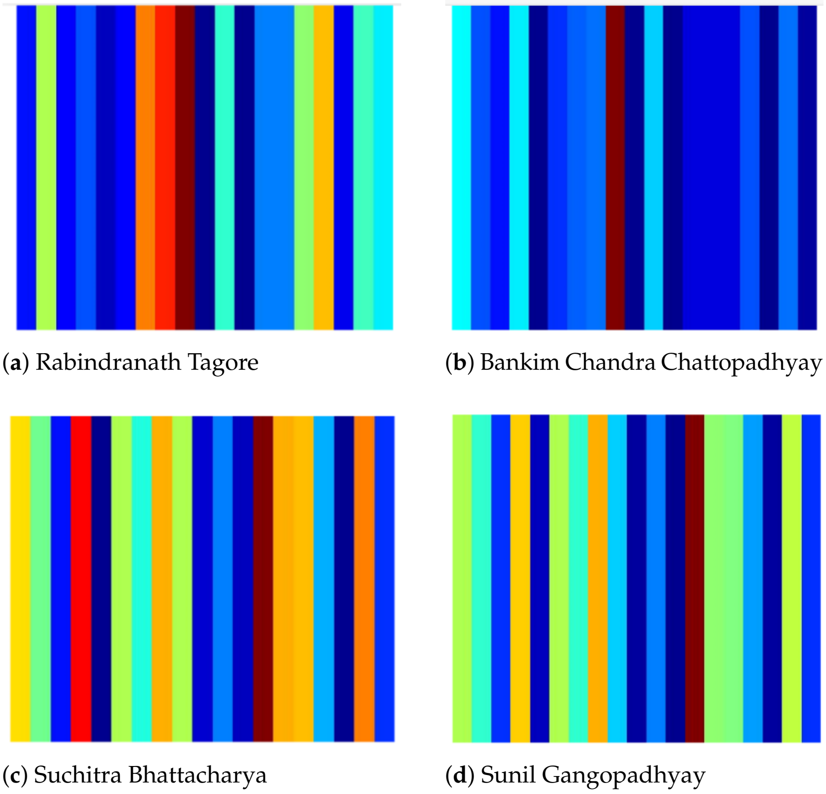
The feature visualization using these three charts for one article of four different authors is presented in Figures 6–8.



(**a**) Rabindranath Tagore (**b**) Bankim Chandra Chattopadhyay

(**c**) Suchitra Bhattacharya (**d**) Sunil Gangopadhyay

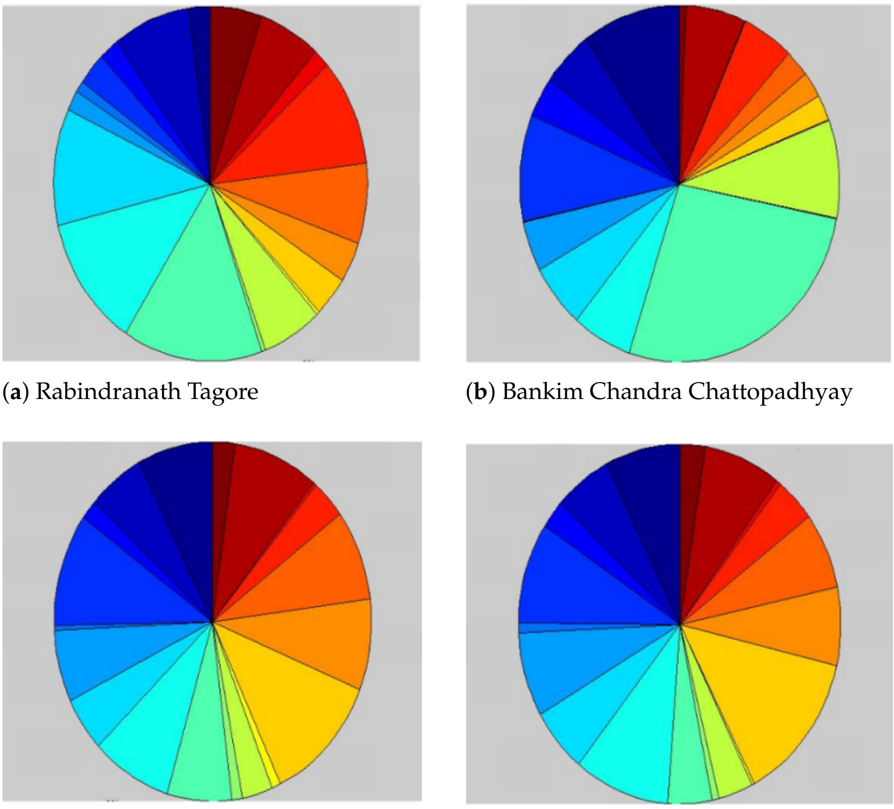
Figure 6. The feature visualizations of one document by four authors using line charts. The x-axis represents the 17 features considered in the experiment. The y-axis represents the feature values obtained for each feature. The line chart follows the default color for the feature values.



(**a**) Rabindranath Tagore (**b**) Bankim Chandra Chattopadhyay

(**c**) Suchitra Bhattacharya (**d**) Sunil Gangopadhyay

Figure 7. The feature visualizations of one document by four authors using imagesc charts. The x-axis represents the 17 features considered in the experiment. The y-axis represents the feature values obtained for each feature. Here, the "jet" theme was used for distinguishing the feature values from one another.



(**a**) Rabindranath Tagore

(**b**) Bankim Chandra Chattopadhyay

(**c**) Suchitra Bhattacharya

(**d**) Sunil Gangopadhyay

Figure 8. The feature visualizations of one document by four authors using pie charts. Each area represents each feature value obtained for 17 features used in the experiment. Here, the "hsv" theme was used for distinguishing the feature values from one another.

3.4. Classification

A convolutional neural network (CNN) is a neural network architecture specially developed to process input images. It is popularly used in various types of problems such as image and video recognition and image classification; it is also used for text-related and time series problems and other applications [35–39]. A CNN is built by stacking three kinds of layers: convolutional layers, pooling layers, and fully connected layers. To these main layers, the dropout layer and the activation function are added. The convolutional layer has a prime role in this architecture as this layer extracts features from the input. It contains convolutional kernels represented by a neuron which works by splitting the images into smaller blocks for the extraction of feature patterns. The multiplication of the input image by a filter of a certain size is performed by the kernels' interaction with the images based on weights. The operation can be portrayed through Equation (16), where $j_d(p,q)$ is an occurrence of the input vector j_d multiplied by the $i_c^j(k,l)$ index of the jth kernel of the cth layer.

$$f_c^k(m,n) = \sum_d \sum_{p,q} j_d(p,q).i_c^j(k,l) \tag{16}$$

The output mapping of the jth kernel is obtained using Equation (17)

$$F_c^j = [f_c^j(1,1),\ldots.,f_c^j(m,n),\ldots.,f_c^j(M,N)] \tag{17}$$

The pooling layer follows the convolutional layer. It decreases the size of the feature map, which reduces computational costs. This operation is done by reducing the relations between the layers and operates independently on each feature map as shown by Equation (18), where Y_c^j determines the pooled feature map of the cth layer for the jth kernel and O_p denotes the pooling operation.

$$Y_c^j = O_p(F_c^j) \tag{18}$$

In this paper, a network was proposed where the inputs were fed to a 32-dimensional convolution layer. The present experiment for training the convolutional neural network model depended on the labeled instances extracted from the handcrafted features for supervised learning [40,41]. The output from this layer was not pooled to avoid a loss of clarity and was passed on to a second convolution layer with 16 dimensions. The dimensions were chosen based on experimental trials. The filter sizes of the 1st and 2nd convolution layers were set to 5 and 3, respectively, after experimental trials. The output of this second layer was max pooled with a window size of 3 followed by a dropout layer, whose result was passed to two dense layers with 256 and 100 dimensions, respectively. The output of the final dense layer was passed on to the fully connected layer. The network was initially trained with images of 100 × 100 pixels and a batch size of 100 instances for 100 epochs. The dropout was set at 50%. The convolution and the first two dense layers had a ReLU activation function, while the final dense layer had a softmax activation function. The architecture of the proposed network is illustrated in Figure 9.

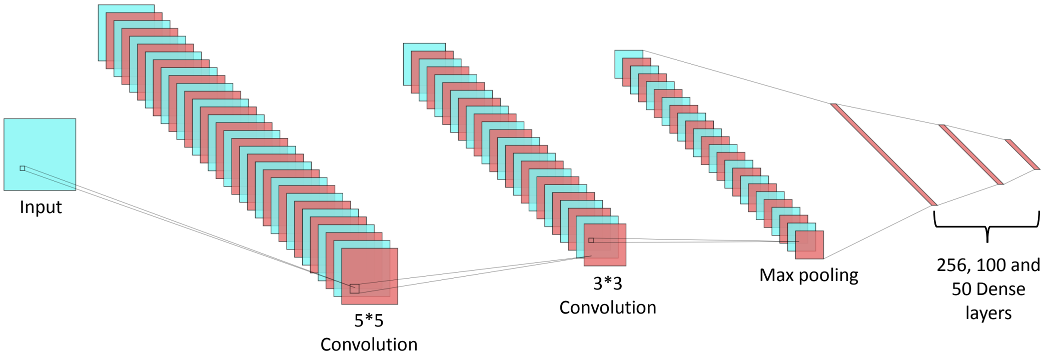


Figure 9. The architecture of the proposed network.

The total number of parameters for each layer are summarized in Table 4.

Table 4. The number of parameters for different layers of the network.

Layers	Parameters
Convolution1	2432
Convolution2	4624
Dense1	3,936,512
Dense2	25,700
Dense3	5050
Total	3,974,318

4. Results and Analysis

This section presents the results obtained on the considered dataset by using the CNN on image-based features. It also presents the analysis of the interclass and intraclass similarities of the articles written by the authors. Furthermore, a comparative analysis of English datasets, state-of-the-art methods, other deep learning models, and commonly used machine learning algorithms is provided.

4.1. Experimental Results

The experiments were carried out on the total dataset comprising 1200 articles written by 50 authors using three different features: 12 statistical-based features, 7 internal features, and a combination of both features (12 + 7). These features were visualized by representing them in a 2D plane, using, as already mentioned, three types of charts (line, imagesc, and pie). Those image-based features were then provided to the CNN network. The results obtained for three charts using three feature sets based on a 80%–20% train–test split are illustrated in Table 5. The experiment was carried out by considering a batch size, image size and epochs of 100 and dropouts of 0.5.

Table 5. Results obtained for three charts using three feature sets.

Types of Charts	Accuracy (in %)		
	Statistical Features	Internal Features	Combination of Both
line	91.92	86.67	93.58
imagesc	86.50	81.67	89.92
pie	91.75	88.42	92.42

The variation in accuracy for a combination of features using a line chart is portrayed through the heat map presented in Figure 10. The x-axis represents the features and the y-axis represents the number of authors. Each cell of a heat map represents a grouping of data. It can be observed that the identification of authors is quite encouraging, as there was either only a slight variation, or the accuracy was maintained for individual authors. In real-world scenarios, the dataset keeps on changing both in terms of volume and variety. To test the performance of the proposed system for such scenarios, the dataset was gradually increased regarding the number of authors from five with a step of five. It was noted that the system maintained its overall accuracy with an increase in the volume of data.

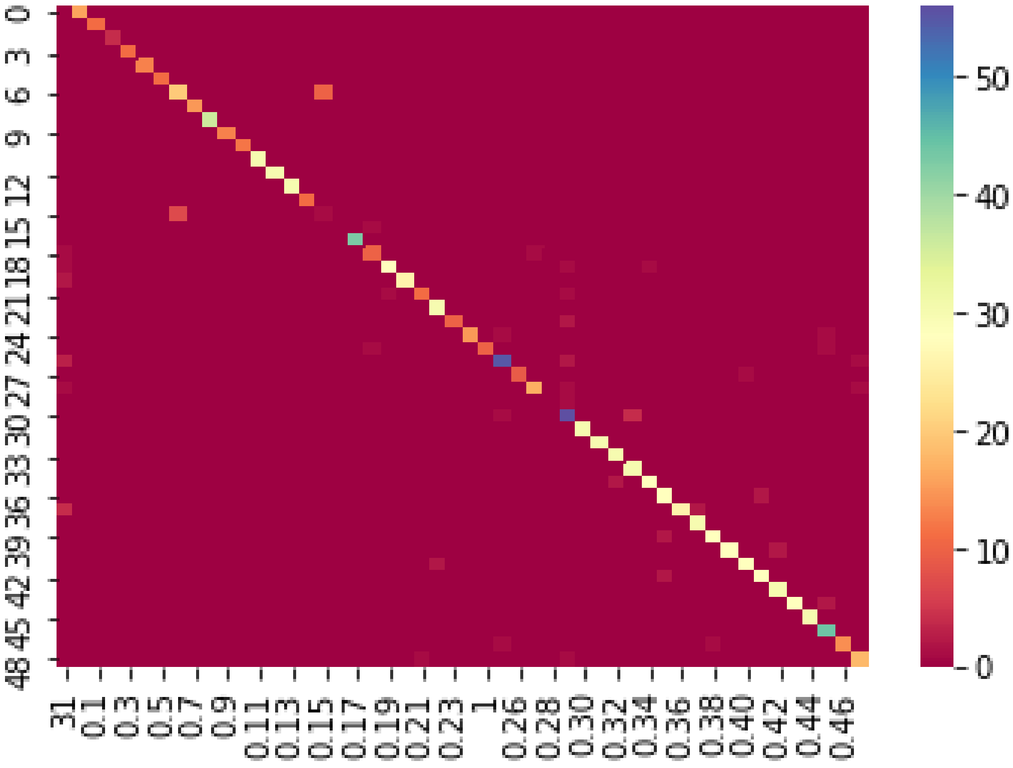


Figure 10. The heat map obtained for the proposed approach.

Since the maximum accuracy of 93.58% was obtained for the line chart using the combination of both feature sets, further experiments were done by tuning the parameters.

The results were obtained for different batch sizes, image sizes, epochs, and dropouts on this feature set, which are provided in Tables 6–9.

Table 6. Results obtained for different batch sizes keeping image size and epochs at 100 and dropout at 0.5.

Batch size	50	100	150	200
Accuracy (in %)	92.75	93.58	93.25	92.92

Table 7. Results obtained for different image sizes keeping batch size and epochs at 100 and dropout at 0.5.

Image size	50	100	150	200
Accuracy (in %)	93.25	93.58	89.75	92.42

Table 8. Results obtained for different epochs keeping batch size and image size as 100 and dropout as 0.5.

Epochs	100	150	200
Accuracy (in %)	93.17	93.58	93.25

Table 9. Results obtained for different dropout values keeping batch size, image size, and epochs as 100, 100, and 150, respectively.

Dropout	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Accuracy (in %)	91.00	90.67	92.50	92.83	93.58	92.58	93.17	93.50	93.25

4.2. Similarity Analysis

We provide a snapshot of the interclass and intraclass similarities in Figure 11. The line chart was considered as it had the maximum accuracy.

4.3. Performance on Datasets of Different Sizes

As already mentioned, the experiments were also expanded on subsets comprising articles from a different number of authors (5, 10, 15, 20, 25, 30, 35, 40, and 45) keeping the type of charts and the feature set the same. Furthermore, the values of the parameters for the CNN architecture for which maximum accuracies had been obtained were kept constant, such as a batch size and image size of 100, 150 epochs, and a dropout of 0.5. The dataset was partitioned based on the number of authors to see how the proposed approach worked for a particular number of articles written by different authors with similar writing patterns. The dataset arranged the authors in a lexicographic manner, so the partition was done based on the same sequence. The partition of the dataset was done incrementally, thus, if an author was selected for a particular set, it would always be considered for increasing datasets. The results obtained for the partitioned datasets are given in Table 10. The deviation in the accuracy from increasing the dataset size is presented in Figure 12. In most cases, the deviation is not very high between successive datasets. This is quite encouraging and also points to the system's ability to handle changes in dataset size and variability.

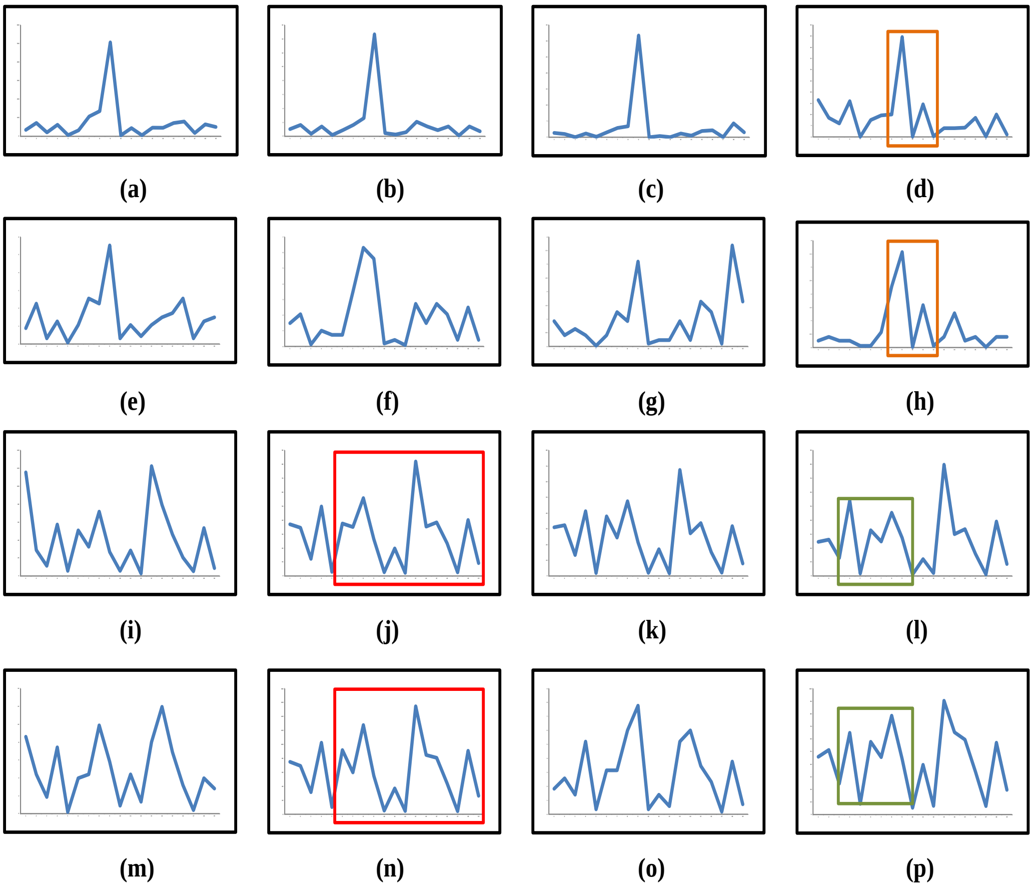


Figure 11. The inter- and intraclass similarity analysis. In this figure, four instances of four different authors are shown ((**a**)–(**d**) from Bankim Chandra Chattopadhyay; (**e**)–(**h**) from Rabindranath Tagore; (**i**)–(**l**) from Suchitra Bhattacharya; and (**m**)–(**p**) from Sunil Gangopadhyay). It can be observed that the interclass similarity is quite high among the authors. There is also a high similarity between different authors such as (**d**) and (**h**) marked in orange boxes, (**j**) and (**n**) marked in red boxes, and (**l**) and (**p**) marked in green boxes, which leads to confusion. Furthermore, an intraclass difference is observed, adding more challenge to our task: the difference can be observed for the pairs (**c**)–(**d**), (**e**)–(**f**), (**i**)–(**j**), and (**n**)–(**o**), all pairs from the same author, which further adds to the chances of misclassification.

Table 10. The results obtained for the partitioned datasets.

No. of Authors	No. of Articles	Accuracy (in %)	Deviation from Past Accuracy
5	55	100.00	—-
10	160	100.00	0.00
15	273	100.00	0.00
20	368	94.84	−5.16
25	468	94.44	−0.40
30	572	91.44	−3.00
35	753	94.29	2.85
40	905	90.50	−3.79
45	1055	93.46	2.96
50	1200	93.58	0.12

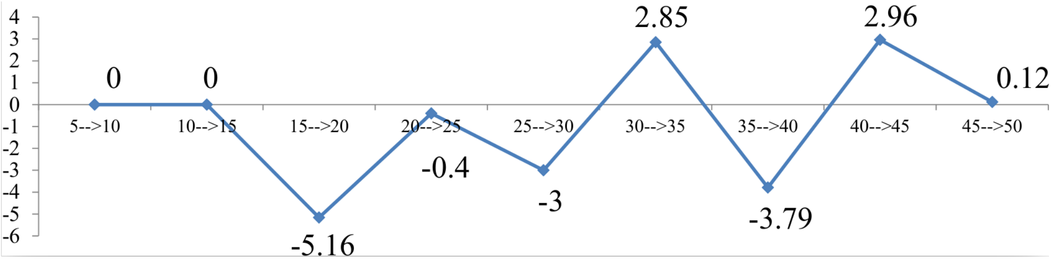


Figure 12. The relative differences in accuracy with increasing number of authors.

Further, the variation in accuracies of author identification for datasets of disparate sizes, i.e., from 5 to 50 authors is presented in Figure 13. The x-axis represents the features and the y-axis represents the number of authors. Each cell of a heat map represents a grouping of data. It is observed that very low accuracies were obtained for some authors. It is also encouraging to observe that there was only a slight variation, or at times the accuracy was maintained, for individual authors when the number of authors was increased. This observation also shows the ability of the system to handle cases where the gradual increase of data over time is a common phenomenon.

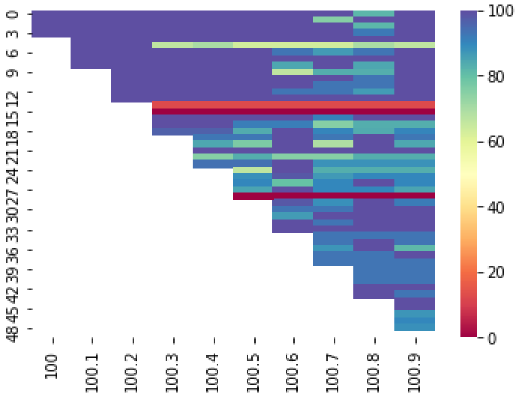


Figure 13. Heat map obtained for datasets of disparate sizes.

4.4. Comparative Studies

In this section, the proposed CNN architecture was compared with other deep learning models, such as Inception and MobileNet, to test the performance of the model on the considered dataset. Furthermore, the result was compared with other popularly used machine learning algorithms to show the efficiency of the deep learning model compared to the supervised learning algorithms. A comparison of the proposed work with the existing state-of-the-art methods is also provided here. Furthermore, to show the language independence of the proposed work, the experiment was tested on an English dataset (C50) as well.

4.4.1. Performance of Established CNN Architectures

To compare the performance of the proposed CNN model, we also employed other CNN architectures: Inception and MobileNet. A brief overview of Inception and MobileNet is described below. These two architectures were selected based on their characteristics by keeping in mind the availability of limited resources.

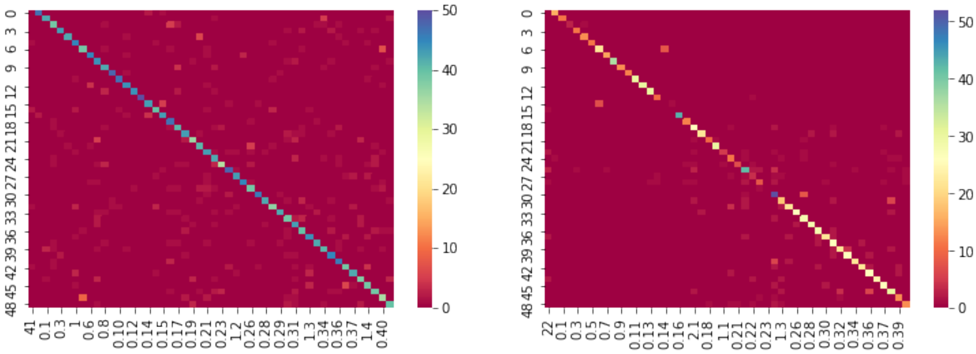
Inception. This architecture resembles a scanty CNN with a condensed structure. It is a blend of 1 × 1, 3 × 3, and 5 × 5 convolutional layers where their outputs are integrated into a single vector, developing the input for the next level. It allows the internal layers to select the dimension of the filters that are required for learning. Each layer is a continual enhancement of the past layer. The number of the convolutional filters of an individual kernel size is kept low because of the effectiveness of a lesser number of neurons. Another characteristic is having a bottleneck layer, which reduces the computation costs. Furthermore, it replaces the fully connected layers with a pooling that moderates the estimates of the filters across the 2D feature map and thoroughly decreases the total number of parameters.

MobileNet. It is devised to productively enhance accuracy while keeping in mind limited resources. It requires less latency and power to encounter the resource limitations of various instances. This model is a heap of independent convolution layers comprising depthwise and pointwise convolutions that separately perform convolution in spatial sizes and input–output channels.

The experiments were performed on both the English (C50 [42]) and Bangla datasets. The results obtained are given in Table 11. The variation in the accuracy of author identification is also shown through the heat maps on Figure 14a,b. The shown heat maps illustrate the model in which the datasets obtained maximum accuracies (for the English dataset, it was the Inception model, whereas for the Bangla dataset, it was the MobileNet model). It is clear from the heat maps that there was confusion between multiple authors for Inception, which was reduced significantly for MobileNet. Though there was confusion among a lesser number of authors, the percentage of confusion was higher, leading to lower interclass accuracies.

Table 11. Results obtained for the other two CNN models.

Model	Parameters	Accuracy (in %)	
		English Dataset	Bangla Dataset
Inception	26,524,202	84.36	77.58
MobileNet	7,425,994	82.96	81.58
Proposed	3,974,318	93.52	93.58



(**a**) English dataset for Inception model

(**b**) Bangla dataset for MobileNet model

Figure 14. The Heat map obtained on the Bangla dataset and English datasets. The heat maps illustrate the model in which the datasets obtained maximum accuracies (for the English dataset it was the Inception model whereas for the Bangla dataset it was the MobileNet model).

4.4.2. Performance of Popular Classifiers

The maximum accuracy was obtained for the total dataset using the combination of both the statistical-based and text-based features. To prove the effectiveness of the proposed approach, this feature set was fed to different machine learning algorithms such as support vector machine (SVM), random forest (RF), multilayer perceptron (MLP), naïve Bayes multinomial (NBM), and rule-based (PART). The results obtained are shown in Figure 15. Comparisons were done keeping the number of dropouts (0.5) and epochs (150) the same for the classification algorithms considered here as those for which the maximum accuracy had been obtained for the CNN.

The parameters used for the SVM were: type of SVM, nu-SVC; type of kernel, sigmoid; degree in kernel function, 3; gamma in kernel function, 1/k; coef0 in kernel function, 0; nu of nu-SVC, 0.5.

The parameters used for the RF were: number of iterations, 1000; minimum number of instances per leaf, 1; minimum variance for split, 1e-3; maximum depth of the tree, 0; and batch size, 100.

The parameters used for the MLP were: number of iterations, 1000; batch size, 100; number of hidden units, 17; learning rate, 0.3; momentum, 0.2; loss function, squared error; activation function, approximate sigmoid.

The default parameters were considered for the NBM model as we used the tokenizer and stopwords removal separately. Furthermore, default values for the stemmer and classifier capabilities were chosen for the experiment.

The parameters used for PART were: confidence threshold for pruning, 0.50; minimum number of objects per leaf, 3; the unpruned decision list was generated; reduced error pruning; and number of folds for reduced error pruning, 4. One fold was used as a pruning set.

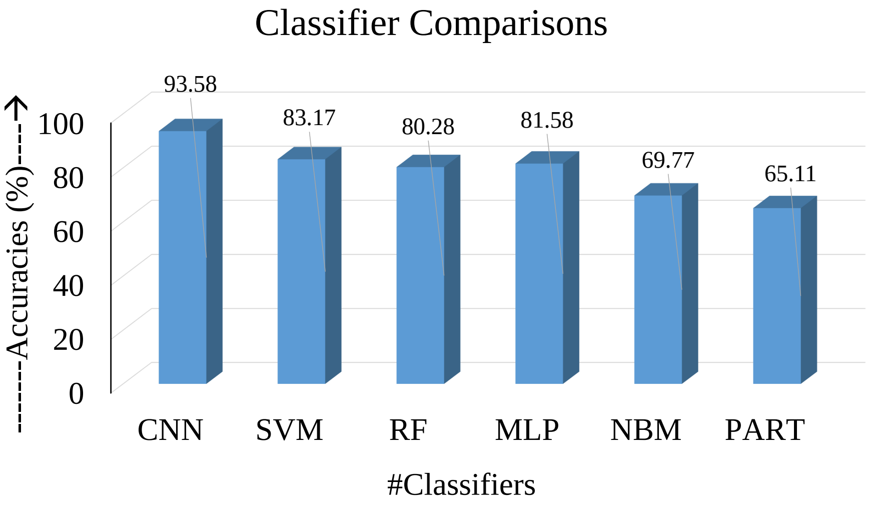


Figure 15. Performance of different popular classifiers.

4.4.3. Performance of Available Works in the Literature

We also compared the performance of the proposed system with other existing works performed in the Bangla language. The experiments were performed following their frameworks and tested on our dataset. Rakshit et al. [19] used semantic-based and stylistic-based features for the identification of poems from four genres based on a support vector machine and achieved 92.3% accuracy. Anisuzzaman and Salam [20] proposed a hybrid model by combining n-gram and naïve Bayes (NB) algorithm and the results showed encouraging performance of the system with a 95% accuracy. The obtained accuracies using our dataset are presented in Table 12. The performance of the proposed model was better than all other existing algorithms when accuracy was concerned. The dataset used in this study was larger when compared to all the other research.

Table 12. The obtained accuracies of the existing systems on our dataset.

Reference	Approach	Accuracy (%)
Rakshit et al.	Semantic and stylistic features + SVM	90.67
Anisuzzaman and Salam	N-gram + NB	84.28
Our approach	Image-based features + CNN	93.58

4.4.4. Performance on the Established Dataset (English)

To test the performance and to prove the language independence of the proposed author identification system, experiments were carried out with one of the most popular and widely used datasets, the C50 dataset, which is a subset of RCV1 [43]. The training and test sets included 2500 documents each (50 per author), nonoverlapping with one another. Here also, the dataset was partitioned into an 80%–20% train–test split for the experiment. The performance of our proposed system was compared with the works proposed by Qian et al. [4] where the authors used article-level GRU and obtained an accuracy of 69.10% on the C50 dataset, Nirkhi et al. [12] worked with word and character unigrams and an SVM classifier on the mentioned dataset and achieved 88% accuracy, and López-Monroy et al. [13] used bag-of-terms model and an SVM and obtained 80.80% accuracy. The accuracy obtained on the said dataset is provided in Table 13 where it can be observed that our system outperformed the existing systems.

Table 13. The results obtained on the C50 dataset using the proposed approach.

Reference	Accuracy (%)
Gupta et al. (2019) [44]	78.10
Nirkhi et al. (2015) [45]	68.76
Our method	93.52

5. Conclusions and Future Work

Using image-based attributes, a deep-learning-based author identification method was suggested in this study. Line, imagesc, and pie charts were utilized to construct the image-based features from 1200 articles written by 50 authors from different generations, using a combination of internal and statistical features. An impressive result of 93.58 percent accuracy for the line chart was obtained. In order to evaluate the applicability of the suggested approach with articles from a variety of authors, experiments were also conducted on the partitioned datasets. Furthermore, to show the language independence of the proposed approach, experiments were conducted on an English (C50) dataset. The system was also tested with an incremental number of authors to simulate real-world scenarios. The system was successful in adapting to the changing datasets and a minimal deviation in the overall accuracy was noted in every step.

In the future, the system will be extended to work with a larger number of articles from various authors of different genres. Experiments will be performed in other languages apart from Bangla and English to judge the language-independent nature of the proposed system. Furthermore, the proposed approach can be further implemented for the author's profiling problem. We also plan to use various techniques, such as clustering, ensemble learning, and extreme learning, to identify authors for respective articles. Furthermore, we would like to explore stylometric features [46], intra and interarticle-based features, graph-based [47], and word embeddings models, respectively, for author identification tasks.

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