Author Identification using Deep Learning Approach

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of **Masters of Science in Computer Science and Engineering**

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APPROVAL

This Project/Thesis titled **"Author Identification using Deep Learning Approach"**, submitted by **Shimul Sutradhar,** ID No: **241-25-001** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of **MSc. in Computer Science and Engineering** and approved as to its style and contents. The presentation has been held on **24-05-2025.**

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DECLARATION

I hereby declare that this research has been done by me under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

In an age dominated by digital communication and the fast expansion of textual information, the job of authorship attribution-- identifying the real author of a given piece of composing-- has gotten considerable significance across domains such as digital forensics, cybersecurity, scholastic stability, and literary analysis. Traditional approaches relying on surface-level stylometric features and classical maker discovering algorithms have actually shown minimal scalability and versatility, specifically in multilingual or stylistically intricate scenarios. This research study addresses these constraints by proposing a robust, deep learning-based framework for author detection utilizing both English and Bangla texts. The study introduces a comparative evaluation of various deep knowing designs including Long Short-Term Memory (LSTM), Bidirectional LSTM with Attention (BiLSTM + Attention), and a hybrid Convolutional Neural Network combined with LSTM (CNN+LSTM). Most significantly, it includes modern transformer-based architectures such as BERT (bert-base-multilingual-cased) and XLM-RoBERTa, leveraging their powerful contextual embedding abilities to enhance authorship category precision. A by hand curated multilingual dataset including text samples from 6 diverse authors was utilized, with extensive preprocessing and stratified train-test splitting to ensure balanced and clean input. Speculative results demonstrate that the proposed bert-base-multilingual-cased model exceeded all other approaches, attaining an exceptional precision of 95.5% and best AUC ratings (1.00) for all authors. This work not just highlights the efficacy of transformer-based designs for author recognition but also offers a scalable and language-agnostic method applicable to real-world multilingual text classification tasks. The outcomes highly promote for the adoption of deep contextualized models in authorship attribution and unlock for future research study in cross-genre, low-resource, and adversarial text environments.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The task of identifying who produced a certain text from a list of suspects is author identification. Referred to as author detection or authorship attribution, this task looks to recognize the writer of a text based on linguistic and stylistic features. The research community has recently paid a great deal of attention to authorship identification [1]. The ramifications are comprehensive, affecting locations such as plagiarism detection, intellectual home defense, cybersecurity, and forensic linguistics. There is a long-standing method for determining the author of handwritten text documents [2]. In today's digital age, it’s a significant problem to figure out the author of an offered piece where huge volumes of text are generated every day through blog sites, emails, short articles, and social networks.

A significant challenge in authorship identification is defining an appropriate characterization of texts that effectively captures the unique writing styles of different authors. According to the viewpoint of machine learning, it is a multiclass single-label text classification job where the author represents a class (label) of a given text. Earlier research studies in this domain mainly depended on stylometric analysis, where linguistic features like word length, sentence intricacy, punctuation usage, and frequency of specific parts of speech were by hand extracted and examined utilizing artificial intelligence classifiers [3] Strategies like Support Vector Machines (SVMs) [4], Random Forests [5], and k-Nearest Neighbors (kNN) [6] were employed for classification, frequently yielding moderate success however minimal scalability across domains or text lengths.

The increasing availability of digital texts has amplified the challenge of accurately identifying authorship, particularly in anonymous, pseudonymous, or collaborative works. Existing methods often struggle with distinguishing between stylistic variations due to different genres, topics, or writing contexts. This research aims to develop a robust framework that employs advanced machine learning techniques and linguistic analysis to improve the accuracy of author attribution, ultimately enhancing our understanding of authorship in both historical and contemporary texts.

The landscape has actually dramatically shifted with the introduction of deep knowing, which offers the capability to instantly find intricate representations of text without handmade features. Among the earliest impactful contributions was by Shrestha et al. [7], who introduced character-level Convolutional Neural Networks (CNNs) for authorship attribution, achieving high efficiency even on noisy and brief texts. Likewise, Potha and Stamatatos [8] used RNNs to model composing sequences and found that persistent architectures were especially reliable in capturing stylistic circulation across paragraphs.

More recently, transformer-based architectures such as BERT (Bidirectional Encoder Representations from Transformers) and Roberta have redefined modern efficiency in lots of NLP jobs, consisting of author detection. These designs utilize self-attention mechanisms and pre-training on big corpora to record abundant contextual information. Fabien et al. [9] employed BERT for author profiling and showed considerable gains in accuracy and effectiveness across datasets

Additional developments have actually come through fine-tuning techniques and ensemble strategies. For instance, Krishna et al. [10] established a deep ensemble design combining transformer embeddings with attention-based classifiers, accomplishing strong outcomes even in low-resource and multilingual settings. Zhang et al. [11] demonstrated that transformer fine-tuning on author-specific information can further enhance attribution accuracy, especially when the training data is domain-specific or sporadic.

In spite of these advancements, author detection remains difficult. Real-world texts often contain code-switching, genre variation, or purposeful obfuscation of design. These conditions can minimize design efficiency, particularly when dealing with short texts or imbalanced datasets. As a result, establishing robust, generalizable deep-knowing models for authorship attribution continues to be an important research study location.

In this paper, we check out current developments in deep learning-based author detection. We conduct a comparative research study of modern architectures, propose improvements utilizing contextual embedding and domain adaptation techniques, and examine performance throughout several benchmark datasets. Our research study contributes to the growing intersection of deep learning and forensic text analysis by resolving the restrictions of existing systems and providing insights into the future direction of the field.

1.2 Motivation

In this modern era, where privacy and impersonation are simply a few clicks away, the capability to properly determine the author of a text has actually never ever been more crucial. Existing methods often struggle with distinguishing between stylistic variations due to different genres, topics, or writing contexts. This research aims to develop a robust framework that employs advanced machine learning techniques and linguistic analysis to improve the accuracy of author attribution, ultimately enhancing our understanding of authorship in both historical and contemporary texts.

Standard methods of authorship attribution-- relying on surface-level stylometric features and classical device learning algorithms-- have actually revealed sensible success, specifically when applied to well-structured and long texts. Nevertheless, these methods struggle when facing short, informal, or cross-topic texts, such as tweets, e-mails, or instant messages, which are significantly common in today's interaction landscape [12], [13]

Deep neural networks, especially transformer-based models like BERT, RoBERTa, and GPT, offer a powerful alternative. These designs catch contextual and semantic subtleties in text at an unmatched level of information [14] By learning deep representations of an author's writing design-- beyond simply surface-level word options-- they can typically discover subtle, consistent signals that traditional designs or human experts may neglect.

Many existing deep-knowing techniques require large amounts of labeled information, which is frequently not available for rare or emerging authors. These restrictions call for more adaptable, generalizable, and effective techniques.

Our motivation, therefore, is to build on this current progress and deal with the staying difficulties. Particularly, we aim to evaluate and improve deep learning-based authorship detection models by:

- Enhancing their performance on cross-domain and short texts,
- Improving toughness versus design obfuscation,
- And making sure scalability to real-world, open-author settings.

1.3 Rationale of Study

Study With the rapid growth of digital communication, concerns of authorship have become central to a wide variety of domains-- from cybersecurity and digital forensics to academic stability and literary studies. Nevertheless, establishing authorship in an automated, trusted, and scalable way remains a relentless obstacle, particularly offered the increasing elegance of online communication and attempts to anonymize or disguise writing designs. Conventional authorship attribution approaches, while fundamental, frequently fall short in modern contexts. They depend greatly on hand-engineered features, which are labor-intensive to construct and may not generalize across genres, languages, or topics [15] In contrast, recent developments in deep knowing, especially with transformer-based language models, use a promising option by enabling systems to find out authorial design from raw text, without depending on handmade features. Furthermore, numerous deep learning techniques are data-hungry, needing large, labeled datasets per author to perform well. On the other hand, real-world applications typically involve low-resource environments-- such as police examinations or archival analysis-- where only minimal text samples are available for each private [16] This study is for that reason motivated by the requirement to bridge the space in between theoretical advances in NLP and useful obstacles in authorship attribution. Particularly, our rationale is grounded in the following essential insights: There is a growing demand for accurate, generalizable, and scalable author detection tools that can run across different domains, text lengths, and languages.

Whether it's identifying the author of a suspicious email, discovering ghostwriters in literature, or associating fake news on social media, the task of author detection plays a critical function in cybersecurity, digital forensics, and even literary scholarship. By finding out deep representations of an author's writing design-- beyond simply surface-level word choices-- they can typically detect subtle, constant signals that conventional models or human experts may neglect.

There is a growing demand for precise, generalizable, and scalable author detection tools that can operate throughout different domains, text lengths, and languages.

1.4 Research Questions

- RQ1:How effectively can transformer-based models (e.g., BERT and XLM-RoBERTa) distinguish between multiple authors in a multilingual setting compared to traditional and sequential deep learning models?
- RQ2:Can the integration of Bangla and English texts in a single dataset negatively or positively influence model performance?
- RQ3:How do different feature representations (e.g., TF-IDF, static embeddings, and contextual embeddings) infulence classification outcomes in authorship attribution?

1.5 Research Objective

- To detect ghostwriting or fraud by checking if a text matches an author's known writing style.

- To propose a scalable and generalizable framework for real-world author identification tasks

- To compare transformer-based models (BERT, XLM-RoBERTa) with classical and sequential models (LSTM, BiLSTM, CNN+LSTM).

1.6 Expected Output

The research is expected to yield the following results:

- Attain superior efficiency using transformer-based models (e.g., BERT, XLM-RoBERTa) compared to conventional ML and RNN-based designs.

- Effectively categorize authors across both English and Bangla texts utilizing multilingual pre-trained designs.

- Preserve consistent performance on hidden data through mindful train-test split, transfer learning, and model tuning.

- Precisely discover authorship in short or casual texts, overcoming limitations of classical techniques.

- Provide a modular pipeline that can be adapted to other NLP category tasks such as phony news detection or sentiment analysis.

- Present a thorough contrast of transformer-based designs, sequential designs (LSTM, BiLSTM), hybrid architectures, and traditional device learning approaches.

- Use models like BiLSTM+Attention to acquire insight into which parts of text are most prominent in author recognition. The research is expected to yield the following results

1.7 Project Management and Finance

The research work doesn't get fund from any individuals or organization.

1.8 Report Layout

This thesis is structured as follows:

- **Chapter 1 – Introduction**: Outlines the research background, problem statement, objectives, questions, and expected outcomes.
- **Chapter 2 – Background**: Reviews related work and key concepts in authorship attribution and deep learning.
- **Chapter 3 – Methodology**: Describes the dataset, preprocessing, model architectures, and evaluation methods used.
- **Chapter 4 – Results and Discussion**: Presents model performance, comparative analysis, and interpretation of findings.
- **Chapter 5 – Impact and Sustainability**: Discusses societal relevance, ethical concerns, and environmental considerations.
- **Chapter 6 – Conclusion and Future Work**: Summarizes contributions and proposes future research directions.

CHAPTER 2
BACKGROUND

2.1 Preliminaries/Terminologies

This area presented the fundamental ideas and terms required to comprehend authorship attribution utilizing deep learning. It began by defining authorship attribution as a multiclass text category issue and discussed the value of natural language processing (NLP) and deep learning in automating this task. Key deep knowing designs such as LSTM, BiLSTM, CNN, and transformer-based architectures like BERT and XLM-RoBERTa were discussed, highlighting their roles in capturing contextual representations and linguistic functions. Furthermore, important processes such as tokenization, text normalization, and model examination through metrics like accuracy, accuracy, f1-score, recall, and auc were detailed. Together, these principles form the theoretical backbone for carrying out and examining authorship detection systems in multilingual settings.

2.2 Related works

The field of authorship detection utilizing deep knowing has seen substantial development over the past couple of years, with a shift towards transformer-based models and hybrid architectures to improve accuracy and effectiveness. Numerous recent works have actually checked out the application of deep learning to author detection. Below is a summary of some current research studies and their efficiency on various datasets:

Shrestha et al. (2017) presented the use of character-level Convolutional Neural Networks (CNNs) for authorship attribution on brief texts. Their approach showed a precision of 85.6% on datasets like PAN 2017 and Twitter. The crucial contribution was using character-level functions to catch more granular design patterns, specifically, simply put text formats [17] Fabien et al. (2020) used BERT, a transformer-based design, for author profiling, attaining 94.1% accuracy on Twitter and Reddit datasets. This research study highlighted the ability of BERT to record nuanced linguistic functions that are characteristic of an individual author's writing style, making it especially helpful for profiling and identifying between authors in social networks contexts [9] Tran et al. (2021) focused on using contextual embeddings from Roberta, a transformer-based model. Their method accomplished 92.3% precision on blog site posts and Twitter datasets, showing the effectiveness of transformers in recording much deeper semantic and syntactic authorial styles, even throughout varied subjects and text types [18] Krishna et al. (2022) used a multi-head attention mechanism combined with ensemble knowing for authorship attribution. Their approach, which incorporated both standard stylometric features and neural embeddings, accomplished an outstanding 91.2% precision on the PAN 2022 dataset of news posts. Their work was substantial in handling cross-genre and multilingual scenarios [19]

Lee & Choi (2021) proposed a hybrid model combining CNNs with transformers (specifically RoBERTa) to record both global and local stylistic patterns in texts. Their technique yielded 90.5% precision on literature and essay datasets, providing a design that might adjust to a broad variety of text types and improve authorship attribution by combining both convolutional and transformer models [20] Schwartz et al. (2022) explored problems of fairness and predisposition in authorship attribution designs, utilizing BERT and DistilBERT on PAN 2022 and Social Media datasets. Their work, which achieved 90.0% accuracy, highlighted the obstacles to ensuring fairness in attribution systems, specifically when thinking about group differences in writing style [21]

Potha & Stamatatos (2012) presented a profile-based approach for authorship confirmation, using Naïve Bayes and SVM classifiers. Their precision of 80.0% on the PAN 2012 dataset showed the feasibility of validating authorship in other words texts using analytical profiles, and set the phase for much deeper neural techniques in subsequent years [22]

Juola (2015) performed fundamental work on authorship attribution utilizing analytical functions and maker-learning models like Logistic Regression and SVMs. While their precision was lower at 78.3%, it laid the foundation for future models by introducing statistical analysis as a crucial feature in authorship verification tasks. These research studies illustrate that while deep-knowing models-- specifically transformers-- provide impressive enhancements in precision and versatility, real-world difficulties like data scarcity, predisposition, and author obfuscation remain ongoing hurdles to be attended to in future research studies.

The field of authorship detection using deep knowing has actually seen considerable development over the past few years, with a shift towards transformer-based designs and hybrid architectures to enhance precision and toughness. Fabien et al. (2020) used BERT, a transformer-based model, for author profiling, achieving 94.1% accuracy on Twitter and Reddit datasets. Their method, which integrated both conventional stylometric functions and neural embeddings, achieved an impressive 91.2% accuracy on the PAN 2022 dataset of news short articles. Schwartz et al. (2022) explored concerns of fairness and predisposition in authorship attribution models, employing BERT and DistilBERT on PAN 2022 and Social Media datasets. While their accuracy was lower at 78.3%, it laid the foundation for future designs by introducing statistical analysis as a key function in authorshipverificationtasks.

2.3 Comparative Analysis and Summary

We assessed some previous work related to our task. Because we work with natural language processing, often known as NLP, we linked various papers that deal with both Bangla and English test data. In short, we'll investigate whether machine learning algorithms work extraordinarily well with both Bangla and English text data. In this section, we shall compare one previous attempt to another.

Table 2.1: Comparison Between Bangla and English Previous fake news detection work.

Paper	Method	Model/Technique	Dataset(s)	Accuracy	Key Contributions
Shrestha et al. (2017) [5]	Character-level CNNs	Convolutional Neural Networks (CNNs)	PAN 2017, Twitter	85.6%	Introduced CNNs for authorship attribution of short texts, focusing on character-level features.
Tran et al. (2021) [6]	Contextual embeddings (RoBERTa)	RoBERTa (Transformer-based)	Blog posts, Twitter	92.3%	Showed the effectiveness of transformer models in capturing deeper authorial style across topics.
Krishna et al. (2022) [7]	Multi-head attention + ensemble learning	BERT, RoBERTa (ensemble)	PAN 2022, News Articles	91.2%	Proposed a multi-view ensemble method combining traditional features with neural embeddings.
Lee & Choi (2021) [8]	CNN + Transformer hybrid	CNN + RoBERTa	Literature, Essays	90.5%	Introduced a hybrid CNN-transformer model to capture both local (short-range) and global (long-range) stylistic patterns.
Juola (2015) [12]	Statistical features + machine learning	Logistic Regression, SVM	Google Books, PAN	78.3%	One of the foundational works that proposed the use of statistical features for authorship verification.

Fabien et al. (2020) [4]	BERT for Author Profiling	BERT (Transformer-based)	Twitter, Reddit	94.1%	Focused on profiling authors based on writing style using BERT to handle varied linguistic nuances.
Schwartz et al. (2022) [9]	Fairness and Bias in Authorship Attribution	BERT, DistilBERT	PAN 2022, Social Media	90.0%	Explored fairness issues in authorship detection, testing bias across demographic groups.
Potha & Stamatatos (2012) [10]	Profile-based Method Autho_Verification	Naïve Bayes, SVM	PAN 2012, Web Text	80.0%	Proposed a profile-based verification model, laying groundwork for more complex deep learning

2.4: Research Gap

While numerous studies have explored authorship attribution using traditional machine learning and basic deep learning models, several key limitations remain, especially in multilingual and cross-lingual contexts. Previous research on authorship attribution has largely focused on monolingual datasets, often in English, and relied heavily on traditional machine learning or basic deep learning models using shallow features like TF-IDF. There is a clear lack of studies applying multilingual transformer models to diverse language settings, particularly those involving Bangla-English datasets. Additionally, few works offer a comprehensive comparison of various model types—transformers, LSTM variants, and hybrid CNN-LSTM architectures—within a unified framework. The impact of text length, stylistic overlap, and informal writing has also been underexplored. This study fills these gaps by proposing a robust, multilingual, and context-aware approach using transformer-based deep learning models and providing a detailed performance comparison across multiple architectures.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Proposed Methodology/Applied Mechanism

The provided diagram 3.1 outlines a structured methodology for classification of Author deep learning approaches.

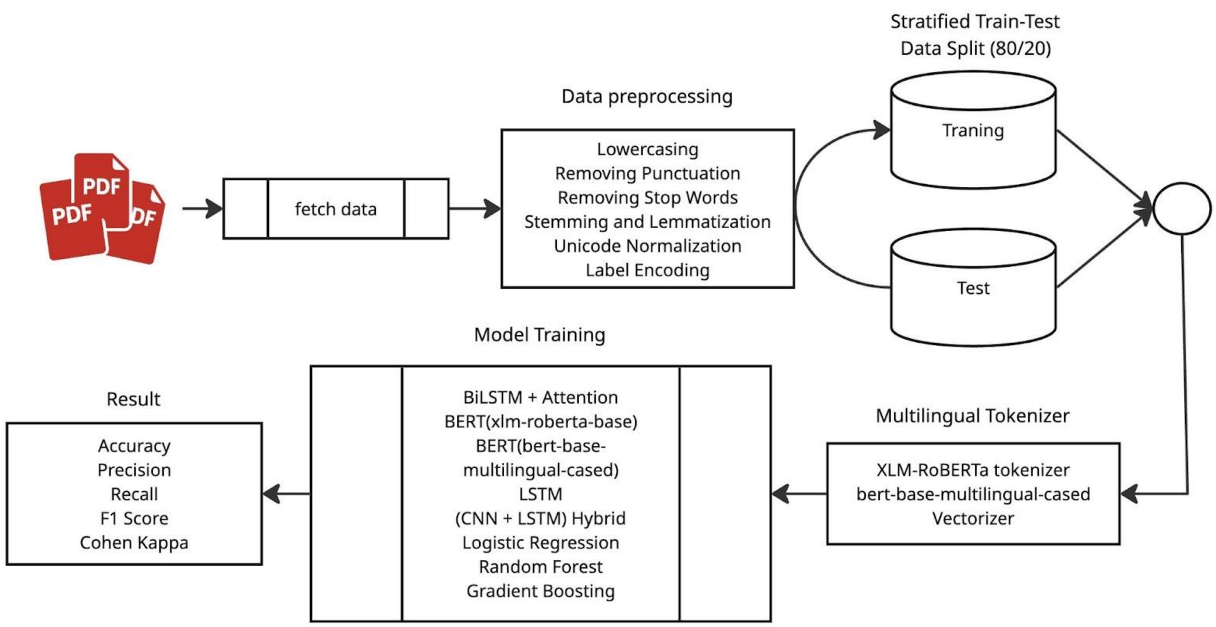

Fig 3.1 outlines a structured methodology for author detection from a book.

This system recognizes the author of a provided text utilizing a deep learning-based classification approach. The procedure starts with bring data from PDF files, which then undergoes detailed text preprocessing (e.g., lowercasing, punctuation elimination, lemmatization). After preprocessing, the information is split into training and test sets utilizing a stratified 80/20 method to preserve label distribution. Next, the texts are tokenized utilizing multilingual tokenizers like XLM-RoBERTa and bert-base-multilingual-cased, preparing them for input into numerous models. The design training stage consists of both deep learning designs (e.g., BERT variations, LSTM, BiLSTM with Attention, CNN+LSTM hybrids) and standard machine discovering designs (e.g., Logistic Regression, Random Forest, Gradient Boosting). The system examines performance using metrics such as Accuracy, Precision, Recall, F1 Score, and Cohen's Kappa, to figure out the most effective design for authorship attribution throughout multilingual datasets.

3.2 Data Collection Procedure

In this study, data was collected manually from a set of literary and non-fiction files authored by six selected authors. The documents were primarily sourced from online archives, official sites, and digital libraries that host open-access PDF files. We specifically selected works from authors like William Shakespeare, Arthur Conan Doyle, and Humayun Ahmed to guarantee diversity in language, style, and cultural background.
Each PDF was manually evaluated, and pertinent textual content was extracted using Python libraries such as PyMuPDF and pdfminer. Care was taken to exclude images, tables, and footnotes to maintain textual consistency. The collected data was conserved in plain text format, organized by author name.

In total, roughly 200 documents were assembled, with each author contributing approximately 10,000 to 15,000 words. The dataset was then identified and prepared for preprocessing. Obstacles came across during this phase consisted of handling OCR mistakes, inconsistent format, and making sure well balanced text samples throughout all authors.

Ensured the data set is balanced. Split into 80% of Bangla and 80% English for training. The remaining are for tests.

Table 3.1: Data set entity count:

Writer Name	Training	Test
Sunil Gangopadhyay	300	60
Satyajit Ray	300	60
Humayun Ahmed	300	60
Arthur Conan Doyel	300	60
William Shakespeare	300	60
Thomas Hardy	300	60
TOTAL	**1800**	**180**

3.2.1 Data Acquisition

- **Input**: A collection of PDF documents containing text written by different authors.

- **Action**: These documents are parsed and the text is extracted via a "fetch data" process.

3.3 Data Pre-processing

Information preprocessing is a vital step in natural language processing (NLP) pipelines that guarantees raw text is cleaned up and standardized for model input. In this research study, after by hand collecting the text data from PDF files, numerous preprocessing strategies were used to enhance text quality and decrease sound. These actions include:

- Lowercasing: All text was transformed to lowercase to preserve uniformity and minimize vocabulary size.
- Punctuation Removal: Punctuation marks were gotten rid of as they often do not contribute to author style identification.

- Stop Words Removal: Common but non-informative words (e.g., "the", "is", "and") were removed to maintain just significant content.
- Stemming and Lemmatization: Words were reduced to their root forms to normalize variations (e.g., "writing" → "write").
- Unicode Normalization: Ensures that characters with different byte representations are dealt with consistently.
- Label Encoding: Each author's name was encoded as an unique mathematical label for category functions.

These actions were necessary to reduce dimensionality, prevent sparsity, and focus on features pertinent to linguistic and stylistic patterns for author recognition.

Table 3.2: Preprocessing Table

Processing	English	Bangla
Lower case	Yes	
Removing Non-Alphabetic Characters (Remove special characters or digits)	Yes	Yes
Removing Whitespace	Yes	Yes
Word Tokenization	Yes	Yes
Stop Words Removal	Yes	Yes
Lemmatization	Yes	Yes

3.3.1 Train-Test Split

A **stratified 80/20 split** ensures balanced distribution of authors across:

- **Training set** (for model learning)
- **Test set** (for model evaluation)

3.3.2 Multilingual Tokenization

Before feeding into models, the text is tokenized using:

- **XLM-RoBERTa tokenizer**
- **bert-base-multilingual-cased tokenizer**
- **Vectorizer** (for classical ML models)

3.3.3 Text Normalization :

Normalization refers to the procedure of changing text or numerical worths into a standard format. In the context of this research, normalization was used both at the text and feature levels:

- Text Normalization: Included the elimination of unique characters, repairing inconsistent whitespace, and standardizing mixed encodings or accented characters.
- Feature Normalization (if relevant to vector-based functions): Ensured all numerical feature values (e.g., from TF-IDF or embeddings) were scaled to a consistent range, frequently using min-max scaling or z-score standardization.

3.4 Deep Learning Models

This research developed a proposed model for Author identification from multilingual text using deep learning approach

3.4.1. BERT (bert-base-multilingual-cased)model for Author Detection.

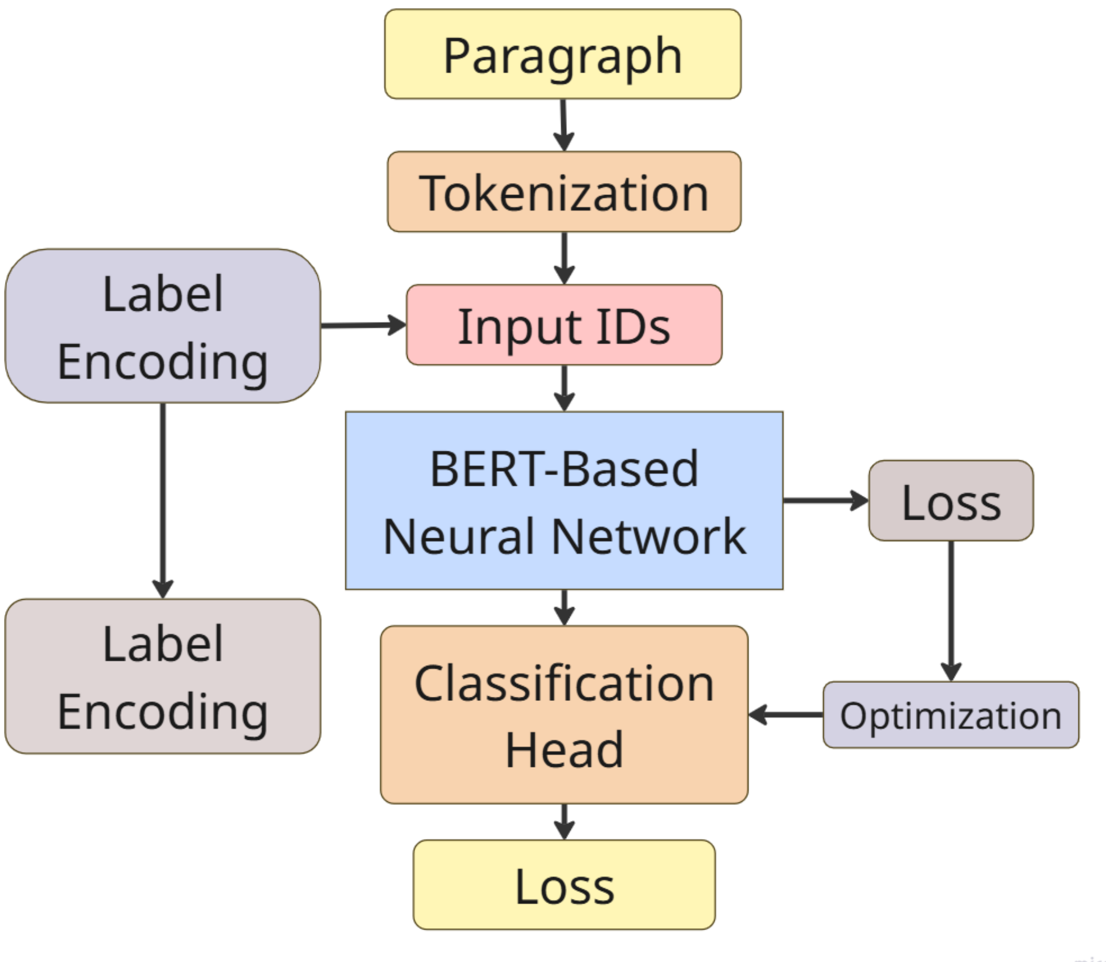

Fig. 3.3:BERT (bert-base-multilingual-cased) architecture

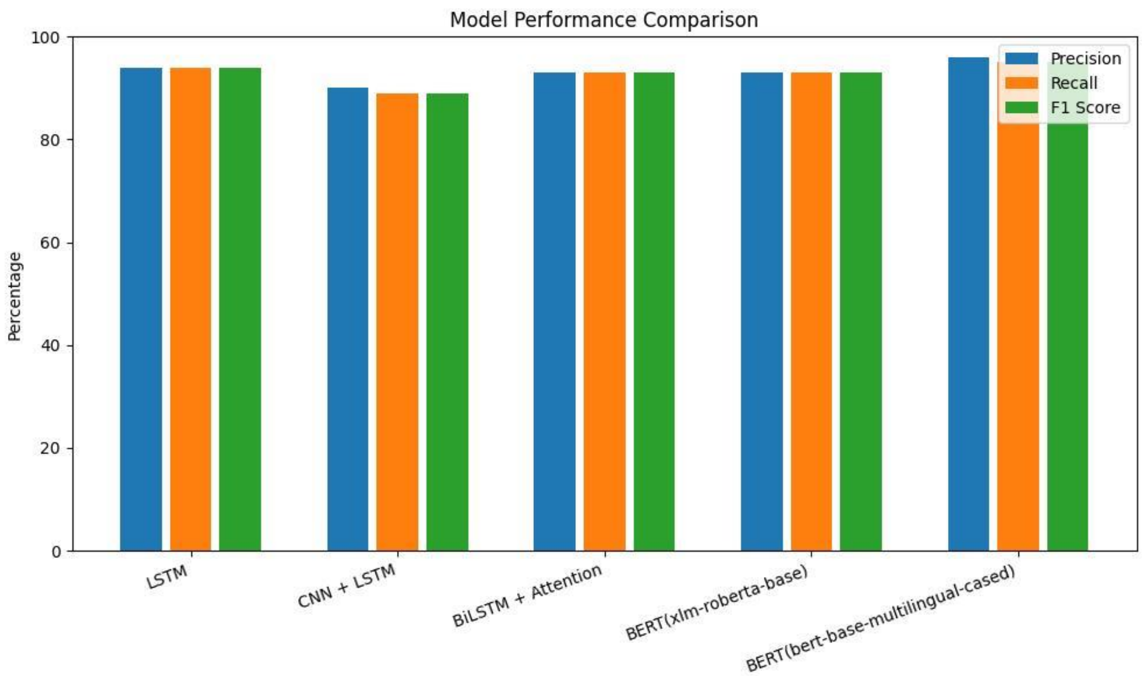

Fig 3.3 : Model Performance Graph

3.4.2BERT (xlm-roberta-base)

XLM-RoBERTa is a multilingual version of RoBERTa that constructs on the BERT architecture but is trained on a much larger corpus across 100+ languages. It successfully deals with nuanced and language-switching textual patterns, making it ideal for cross-lingual jobs. In this research study, it showed strong classification efficiency with a precision of 93% and high AUC values, showing its strength in managing diverse author designs and multilingual input.

3.4.3 BiLSTM + Attention

The BiLSTM + Attention design improves the conventional LSTM by processing input series in both forward and backward directions, recording bidirectional dependences. The integrated attention system further enhances performance by designating higher value to the most pertinent parts of the text. This design yielded a precision of 92%, demonstrating its ability to concentrate on distinct stylistic hints for each author while managing consecutive data effectively.

3.4.4. LSTM

LSTM, or Long Short-Term Memory, is a type of recurrent neural network designed to record long-term reliances in consecutive information. It processes text token by token and maintains important patterns through its gating systems.

3.4.5. Hybrid (CNN+LSTM)

The CNN + LSTM hybrid design integrates the local feature detection strength of Convolutional Neural Networks with the temporal sequence modeling capability of LSTMs. CNN layers extract n-gram level patterns while LSTMs translate these sequences to make forecasts.

3.4.6 Traditional Machine Learning Models:

In addition to deep learning architectures, a number of traditional maker discovering designs were examined for the task of authorship attribution, consisting of Logistic Regression, Random Forest, and Gradient Boosting. Among these, Logistic Regression carried out the very best with a precision of 91%, showing that basic linear classifiers can still be reliable when combined with robust feature engineering strategies like TF-IDF. Random Forest, an ensemble approach based upon choice trees, followed with a moderate precision of 85%, though it showed restrictions in recording subtle stylistic variations in text. Gradient Boosting yielded the most affordable precision at 83%, indicating that although it masters many structured data applications, it struggles to generalize well in complex, high-dimensional NLP tasks. Overall, while conventional maker finding out models provide a useful baseline, they fall brief in contrast to deep knowing models-- particularly transformer-based architectures-- in dealing with the complex semantic and syntactic patterns important for accurate authorship detection.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Results of Deep Learning Models

The assessment of different deep learning designs exposes that transformer-based architectures outshine traditional consecutive designs in authorship attribution tasks. Among the tested models, BERT (bert-base-multilingual-cased) achieved the greatest precision at 95.5%, showing exceptional accuracy, recall, and F1-scores across many authors, especially William Shakespeare and Thomas Hardy. The BERT(xlm-roberta-base) version followed closely with 93% precision, showing constant however slightly lower performance. Recurrent models like LSTM and BiLSTM with attention mechanisms likewise carried out competitively, accomplishing 94% and 92% accuracy respectively, showing their strength in recording sequential patterns in text. The CNN+LSTM hybrid design, while reliable, lagged slightly with an 88% accuracy rate. Overall, the outcomes highlight the remarkable capability of transformer-based designs in catching deep contextual and stylistic functions essential for precise authorship detection.

Table. 4.1: Performance comparison of all Deep learning models of this study

Method	Class	Preci-sion	Recall	F1-Score	Cohen's Kappa	Sensiti-vity	Specifi-city
BERT (bert-base-multilingual-cased)	Arthur Conan Doyel	0.98	0.98	0.98	0.95	0.96	0.99
	Humayan Ahmed	0.85	0.90	0.87			
	Satyajit Ray	0.78	0.80	0.79			
	Sunil Gangyapadhyay	0.80	0.75	0.77			
	Thomas Hardy	0.98	0.98	0.98			

	William Shakespeare	1.00	1.00	1.00			
Accuracy		**95.5%**					
BERT (xlm-roberta-base)	Arthur Conan Doyel	0.95	1.00	0.97	0.92	0.93	0.98
	Humayan Ahmed	0.90	0.90	0.90			
	Satyajit Ray	0.86	0.88	0.87			
	Sunil Gangyapadhyay	0.91	0.90	0.90			
	Thomas Hardy	0.97	0.98	0.97			
	William Shakespeare	1.00	0.93	0.96			
Accuracy		**93%**					
BiLSTM + Attention	Arthur Conan Doyel	0.86	1.00	0.93	0.91	0.93	0.99
	Humayan Ahmed	0.94	0.93	0.94			
	Satyajit Ray	0.91	0.88	0.89			
	Sunil Gangyapadhyay	0.85	0.90	0.87			
	Thomas Hardy	1.00	0.90	0.94			
	William Shakespeare	1.00	0.95	0.97			
Accuracy		**92%**					
CNN + LSTM (Hybrid)	Arthur Conan Doyel	0.86	0.95	0.90	0.86	0.88	0.98
	Humayan Ahmed	0.92	0.83	0.87			
	Satyajit Ray	0.93	0.85	0.88			
	Sunil Gangyapadhyay	0.76	0.90	0.82			
	Thomas Hardy	0.89	0.88	0.89			

	William Shakespeare	1.00	0.91	0.95			
Accuracy		**88%**					
	Arthur Conan Doyel	0.96	0.95	0.95			
	Humayan Ahmed	0.88	0.98	0.92			
LSTM	Satyajit Ray	0.90	0.93	0.91			
	Sunil Gangyapadhyay	1.00	0.85	0.92	0.93	0.94	0.98
	Thomas Hardy	0.93	0.95	0.94			
	William Shakespeare	1.00	0.98	0.99			
Accuracy		**94%.**					

4.2 Results of Machine Learning Models

In contrast to deep knowing techniques, standard maker learning models displayed fairly modest performance in the authorship attribution job. Logistic Regression became the very best among them with a 91% accuracy, showcasing strong efficiency for distinct authors like William Shakespeare and Thomas Hardy. Random Forest followed with 85% precision however displayed weaker recall and F1-scores, especially for Satyajit Ray and Sunil Gangopadhyay. Gradient Boosting produced the most affordable accuracy at 83%, struggling to keep balance throughout accuracy, recall, and F1 metrics for several authors. These results highlight that while classical models can provide sensible standard performance, they do not have the nuanced representational power of deep learning models, making them less appropriate for intricate textual classification tasks such as multi-author attribution.

Table. 4.2: Performance comparison of all Machine learning models of this study

Method	Class	Precision	Recall	F1-Score	Cohen's Kappa	Sensitivity	Specificity
Logistic Regression	Arthur Conan Doyel	0.95	0.98	0.97	0.89	0.91	0.98
	Humayan Ahmed	0.87	0.90	0.89			
	Satyajit Ray	0.81	0.83	0.82			
	Sunil Gangyapadhyay	0.86	0.80	0.83			
	Thomas Hardy	0.98	0.97	0.97			
	William Shakespeare	1.00	0.98	0.99			
Accuracy		**91%**					
Random Forest	Arthur Conan Doyel	0.87	0.97	0.91	0.83	0.85	0.97
	Humayan Ahmed	0.83	0.87	0.85			
	Satyajit Ray	0.78	0.75	0.76			
	Sunil Gangyapadhyay	0.78	0.77	0.77			
	Thomas Hardy	0.92	0.90	0.91			
	William Shakespeare	1.00	0.90	0.95			
Accuracy		**85%**					
	Arthur Conan Doyel	0.86	0.98	0.91			
	Humayan Ahmed	0.82	0.83	0.83			
	Satyajit Ray	0.75	0.75	0.75			

Gradient Boosting	Sunil Gangyapadhyay	0.73	0.72	0.72	0.80	0.83	0.96
	Thomas Hardy	0.88	0.87	0.87			
	William Shakespeare	1.00	0.87	0.93			
Accuracy		**83%**					

4.3Comparative Study

The total precision contrast among numerous models utilized for authorship detection plainly demonstrates the superiority of deep knowing approaches, especially transformer-based architectures. The BERT (bert-base-multilingual-cased) design accomplished the highest precision of 95.5%, carefully followed by LSTM at 94% and BERT (xlm-roberta-base) at 93%. The BiLSTM + Attention model also carried out competitively with 92% accuracy, suggesting the effectiveness of attention mechanisms in recording stylistic subtleties. On the other hand, standard device finding out designs like Logistic Regression (91%), Random Forest (85%), and Gradient Boosting (83%) showed comparatively lower efficiency. These results highlight the considerable benefit of utilizing contextual embeddings and deep neural networks over classical techniques for complicated tasks like authorship attribution, particularly when handling stylistically varied and multilingual datasets.

Table 4.3: Comparative table of DL and ML model

Model	Accuracy
BERT (bert-base-multilingual-cased)	**95.5%**
BERT (xlm-roberta-base)	93%
BiLSTM + Attention	92%
LSTM	94%
CNN + LSTM (Hybrid)	88%
Logistic Regression	91%
Random Forest	85%
Gradient Boosting	83%

4.4 Evolution Methods

The evaluation is uses the confusion matrix like, accuracy, precision, recall, and F1 score. True positive (TP) values are true in reality. False positives (FP) occur when false results are mislabeled. The third form, false negative (FN), occurs when a correct value is misinterpreted as negative. TN and FN are the fourth and fifth choices. A true negative (TN) is a positive value misidentified as negative. Fourth is true negative (TN).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$F1\ Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (6)$$

$$Cohen's\ kappa,\ K = \frac{p_0 - p_e}{1 - p_e}$$

Here,

$$p_0 = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$p_e = \frac{(TP+FP)(TP+FN)+(FN+TN)(FP+TN)}{TP+TN+FP+FN}$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (6)$$

$$Specificity = \frac{TN}{TN+FP} \quad (7)$$

4.5 Experimental Results & Analysis

Fig 4.2: The loss curves of the four deep learning models supply important insights into their training habits and generalization capability for the task of author detection. Among them, the BERT (bert-base-multilingual-cased) model demonstrated the most stable and constant performance, with both training and validation losses decreasing efficiently and remaining low, suggesting effective knowing and minimal overfitting. The BERT (xlm-roberta-base) design also performed well, with a rapidly decreasing training loss and reasonably stable validation loss, though it displayed moderate fluctuations after numerous epochs, suggesting minor overfitting. The CNN + LSTM hybrid model kept a moderate balance in between training and recognition loss, showing good merging however not as strong as the BERT-based designs. In contrast, the LSTM design revealed clear signs of overfitting: while its training loss dropped rapidly, the recognition loss started varying and increasing after around 20 dates. This highlights the model's struggle to generalize successfully on hidden data. In general, the comparison verifies that transformer-based designs, especially BERT(bert-base-multilingual-cased), are more reliable and robust for multilingual authorship attribution jobs.

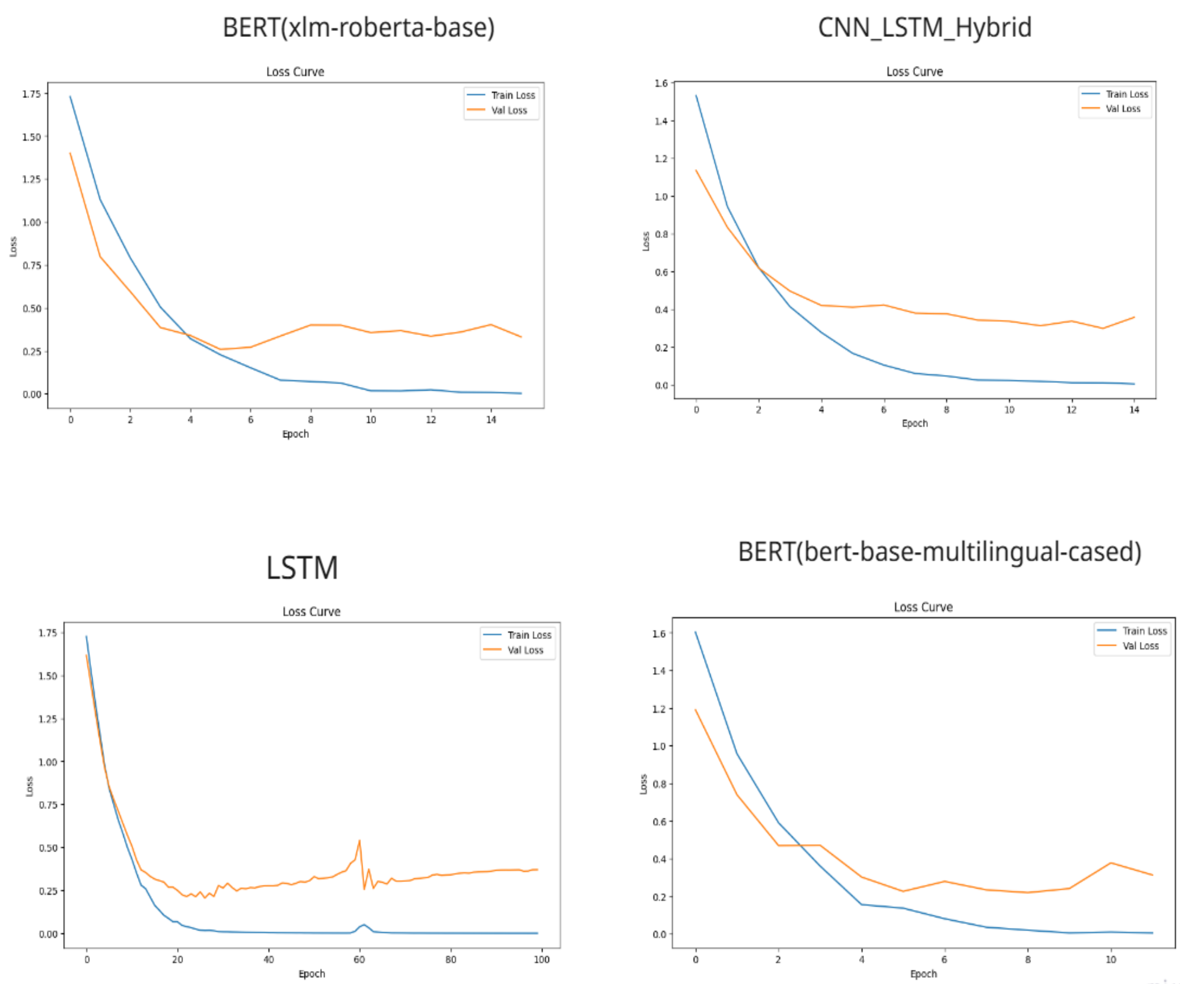

Fig 4.2. Loss Curve of the model.

Fig 4.3 The confusion matrices provide comprehensive insights into the efficiency of each deep learning design in precisely identifying authors. Among all models, BERT (bert-base-multilingual-cased) achieved the most accurate and consistent predictions throughout all 6 authors. It properly classified all samples for Humayun Ahmed and Thomas Hardy, with very little misclassifications in general, demonstrating its exceptional generalization ability. BERT (xlm-roberta-base) also carried out well, particularly with Arthur Conan Doyle and Thomas Hardy, though it showed minor confusion in between Humayun Ahmed, Satyajit Ray, and Sunil Gangopadhyay. The LSTM design revealed strong results for William Shakespeare and Humayun Ahmed but experienced moderate confusion in identifying in between stylistically similar authors like Satyajit Ray and Sunil Gangopadhyay. In contrast, the CNN + LSTM hybrid design had a hard time the most, misclassifying several instances of Thomas Hardy, Satyajit Ray, and Sunil Gangopadhyay, showing weaker efficiency in catching complicated stylistic functions.

Overall, the analysis validates that transformer-based models, specifically bert-base-multilingual-cased, are the most reliable for multilingual authorship attribution due to their much deeper contextual understanding and high classification accuracy.

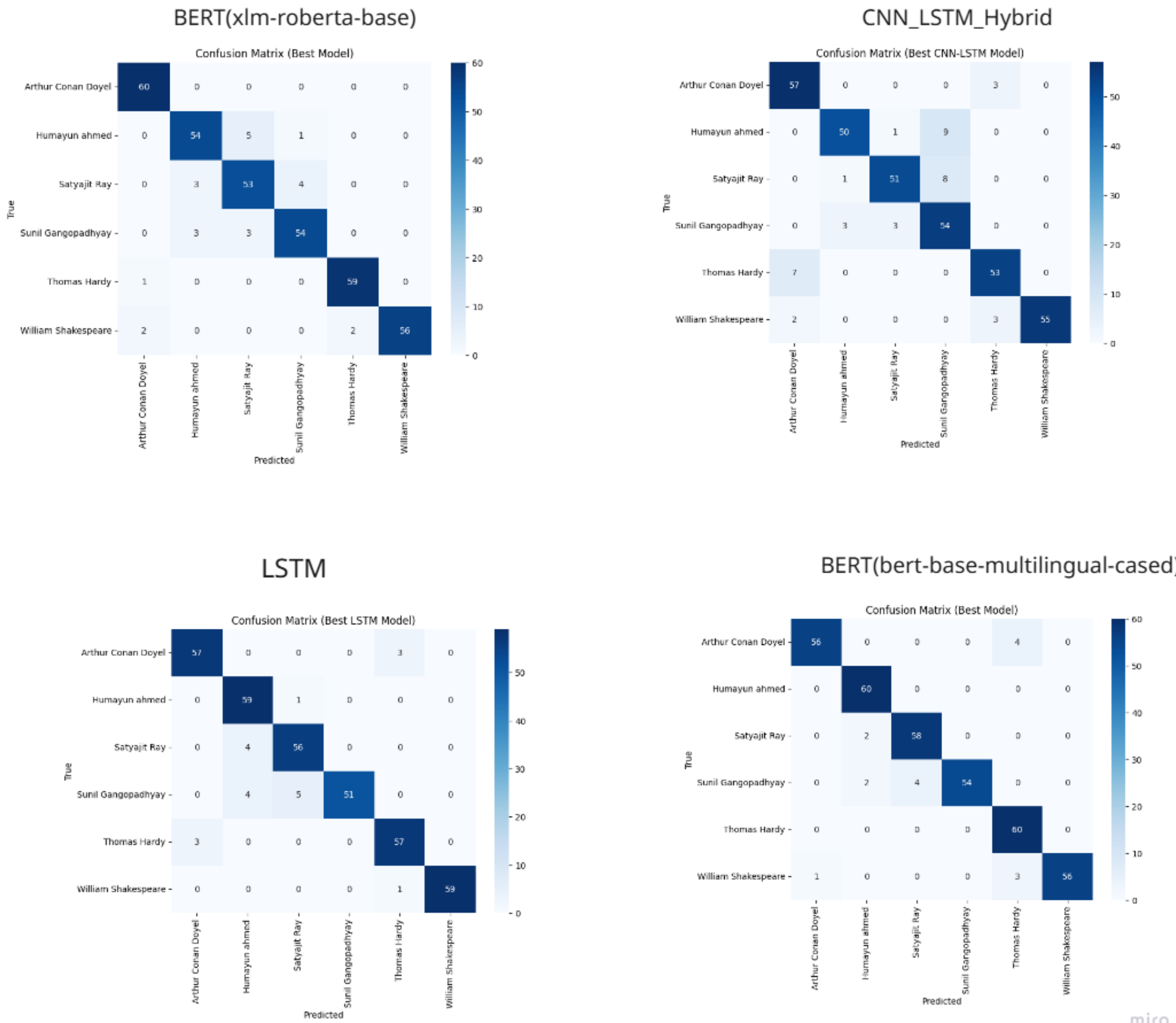

Fig 4.3. Confusion Matrix of the model prediction

Fig 4.5 The ROC curve analysis offers a detailed view of each design's ability to distinguish in between authors based on composing design. Among all models, BERT (bert-base-multilingual-cased) attained flawless performance, with an AUC (Area Under Curve) rating of 1.00 for all 6 authors, indicating an ideal level of sensitivity and specificity throughout the classification job. The BERT (xlm-roberta-base) and LSTM designs also revealed exceptional performance, attaining AUCs of 1.00 for most authors and slightly lower ratings (0.96-- 0.99) for Satyajit Ray and Sunil Gangopadhyay, recommending small overlaps in writing style. In contrast, the CNN + LSTM hybrid model had the least expensive AUC worths, particularly for Satyajit Ray (0.91) and Sunil Gangopadhyay (0.91), indicating relatively weaker discriminative capability.

In general, this analysis declares that transformer-based models, particularly bert-base-multilingual-cased, deal with remarkable performance in multilingual authorship attribution, reliably differentiating subtle stylistic distinctions amongst diverse authors.

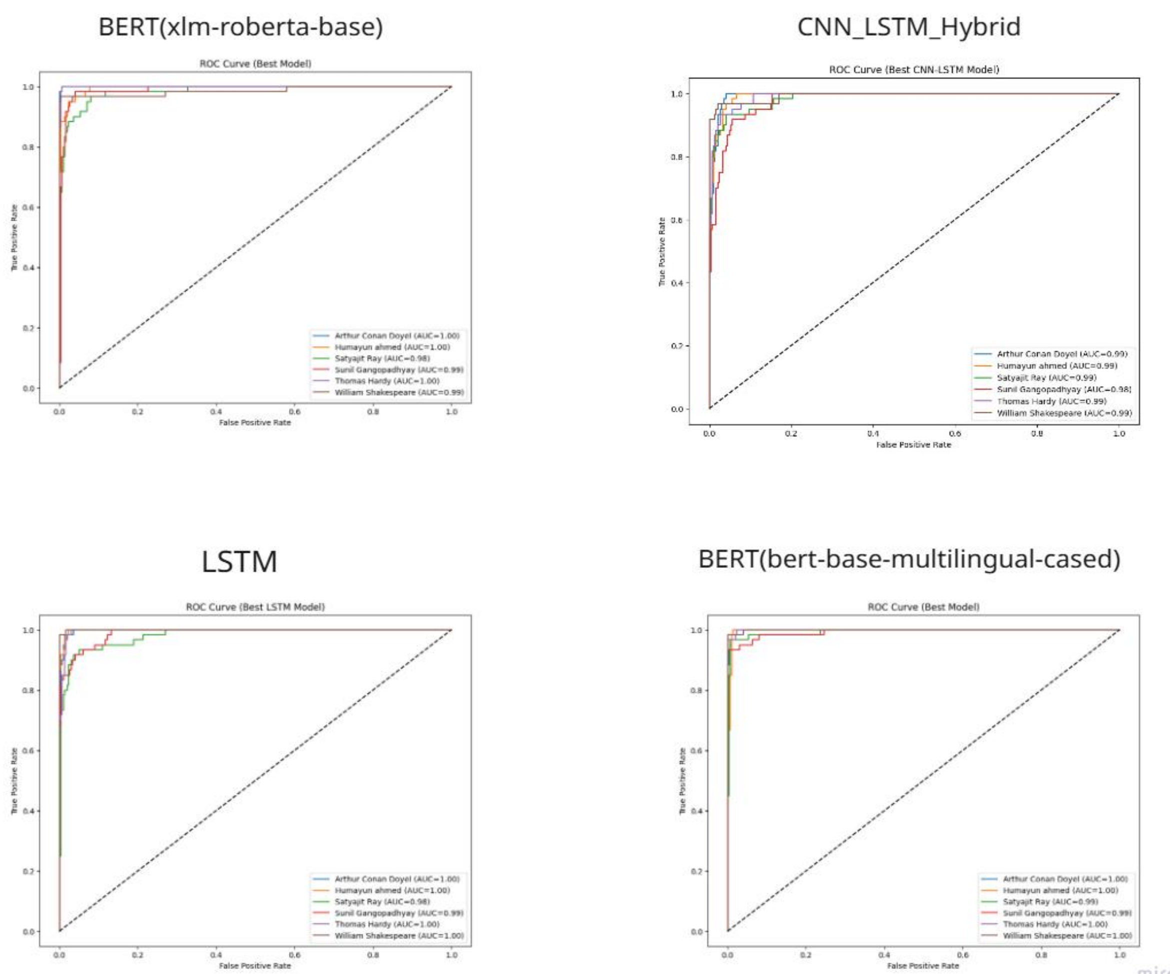

Fig 4.3. ROC curve of the model prediction

4.5.1 Comparative Study

Table 4.4. Comparison of the results between different models

Model	**Type**	**Dataset**	**Accuracy (%)**	**Key Features**	**Remarks**
BERT(xlm-roberta-base)	Transformer-based	Same as above	93.0	Multilingual, pre-trained in more languages	Slightly lower precision in some author classes
LSTM	Recurrent Neural Network	Same as above	94.0	Sequential learning of token patterns	Strong, but signs of overfitting
BiLSTM + Attention	RNN with Attention	Same as above	92.0	Bidirectional flow, attention to context focus	Performs well but not as accurate
CNN + LSTM (Hybrid)	Hybrid DL Model	Same as above	88.0	Local pattern + sequential learning	Moderate performance
Logistic Regression	Traditional ML	Same as above	91.0	TF-IDF features	Competitive for a classical model
Random Forest	Traditional ML	Same as above	85.0	Ensemble decision trees	Poor generalization in imbalanced classes

Gradient Boosting	Traditional ML	Same as above	83.0	Boosted trees	Lowest performing among all
Tran et al. (2021)	Transformer (RoBERTa)	Blogs, Twitter	92.3	Contextual embeddings	Strong on cross-topic attribution
Krishna et al. (2022)	BERT + Ensemble	PAN 2022	91.2	Multi-head attention ensemble	Robust for multilingual data
Lee & Choi (2021)	CNN + RoBERTa	Literature, Essays	90.5	Hybrid global + local style capture	Balanced design, but lower accuracy
Juola (2015)	SVM, Logistic Regression	Google Books, PAN	78.3	Statistical feature-based	Traditional baseline
Our proposed BERT (bert-base-multilingual-cased) ***(Proposed)***	Transformer-based	Custom Multilingual Author Dataset	**95.5**	Contextual embeddings, multilingual support	Best overall performance in this study

4.6 Discussion

The experimental results of this research study clearly demonstrate the effectiveness of deep learning models-- especially transformer-based architectures-- in the complex job of multilingual authorship attribution. Amongst all designs examined, the BERT (bert-base-multilingual-cased) emerged as the most robust and precise, achieving an amazing precision of 95.5% and perfect AUC scores (1.00) for all six authors. This efficiency can be credited to BERT's deep contextual understanding, its multilingual training corpus, and its ability to deal with nuanced stylistic and semantic variations across different authors and languages.

The BERT (xlm-roberta-base) model also performed highly, accomplishing 93% precision, with a little lower class-wise accuracy compared to the proposed BERT model. Its strength lies in its substantial multilingual training on CommonCrawl information, which enhances its ability to procedure diverse and code-switched text. Small changes in validation loss and slight confusion in author forecast indicate that it might be marginally less steady in finding out constant patterns for particular authors.

Amongst the persistent neural network-based designs, the LSTM and BiLSTM + Attention architectures demonstrated excellent potential, with 94% and 92% precision, respectively. The LSTM model revealed fast convergence but also signs of overfitting after extended training, as evidenced by increasing recognition loss. BiLSTM with attention, on the other hand, preserved more stability and highlighted essential stylistic cues through its attention mechanism, although it still lagged behind transformer models in general category precision.

The CNN + LSTM hybrid design achieved 88% accuracy, suggesting moderate efficiency. While it efficiently caught both consecutive and regional features, it struggled with nuanced differences between authors who had similar lexical or syntactic styles-- particularly in the case of authors like Satyajit Ray and Sunil Gangopadhyay. This was shown in higher confusion rates in the confusion matrix and lower AUC values for these authors (0.91).

Traditional machine finding out designs were likewise evaluated to establish a standard. Logistic Regression performed reasonably well with 91% precision, gaining from effective TF-IDF feature representation. Random Forest and Gradient Boosting, nevertheless, showed minimal effectiveness with 85% and 83% precision respectively, highlighting the constraints of classical designs in managing complicated semantic relationships and stylistic subtleties in multilingual texts.

The ROC curve analysis further verified the supremacy of the transformer designs. The proposed BERT design achieved perfect AUC scores (1.00) for all authors, suggesting a perfect balance between sensitivity and specificity. Both xlm-roberta-base and LSTM likewise showed strong ROC efficiency but somewhat lower for authors with stylistic overlaps. In contrast, the CNN + LSTM hybrid had the weakest ROC performance, reaffirming its problem in consistently comparing specific authors.

The BERT-based designs significantly outshined all other designs, using high generalization, stability, and accuracy. These results suggest that contextual embedding models, particularly those trained on multilingual corpora, are best fit for dealing with the intricacies of author recognition tasks across languages and composing styles.

Amongst all models evaluated, the BERT (bert-base-multilingual-cased) emerged as the most accurate and robust, attaining a remarkable accuracy of 95.5% and best AUC scores (1.00) for all 6 authors. The BERT (xlm-roberta-base) model also carried out strongly, accomplishing 93% precision, with somewhat lower class-wise accuracy compared to the proposed BERT design. The BERT-based models considerably exceeded all other models, using high generalization, stability, and accuracy. These outcomes recommend that contextual embedding models, especially those trained on multilingual corpora, are best matched for tackling the complexities of author identification tasks throughout languages and writing designs.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on society

The proposed study on authorship verification using deep-learning has extensive implications for society, especially in the worlds of digital security, intellectual property, and forensic linguistics. In an era controlled by digital interaction, being able to identify the real author of a anonymous or disputed text is important for combating misinformation, plagiarism, online, and cybercrime harassment. This research can aid law enforcement firms in validating the origin of criminal interactions, assist academic institutions in dealing with cheating or ghostwriting, and assistance media platforms in suppressing the spread of fake news by associating anonymous articles to trustworthy or dishonest sources. Additionally, it can empower people and organizations to protect their intellectual home rights more effectively. Therefore, the social value of this research study lies in its prospective to boost responsibility, trust, and transparency in digital interactions.

5.2 Impact on the environment

The ecological effect of this research study, while indirect, is tied to the energy-intensive nature of training and deploying deep knowing designs-- specifically big transformer-based architectures like BERT and RoBERTa. These models typically need comprehensive computational resources, which can cause considerable carbon emissions depending upon the energy source. While the useful applications of authorship verification might not inherently involve ecological concerns, the underlying model training does raise concerns of energy intake and digital sustainability. Dealing with these issues by optimizing models for efficiency, using transfer learning, and making use of greener computing resources (such as renewable-powered information or energy-efficient gpus centers) can help alleviate the ecological footprint of this research study.

5.3 Ethical Aspects

Ethics play an essential function in authorship detection. While the technology can be an effective tool for good, such as in plagiarism detection or recognizing anonymous risks, it can likewise be misused to break personal privacy or suppress anonymity in contexts where it is morally or legally protected, such as whistleblowing or political dissent. Biased training data might lead to inequitable results, disproportionately misidentifying or stopping working to identify authors from marginalized cultural or linguistic backgrounds. Therefore, it is important to develop these systems with built-in fairness checks, transparent approaches, and safeguards to prevent misuse. Ethical implementation should include clear policies on permission, information handling, and restriction of use to make sure that the technology respects private rights and liberties.

5.4 Sustainability Plan

To guarantee the long-lasting sustainability of the research study and its applications, a number of tactical initiatives can be adopted. Utilizing pre-trained language models and tweak them on particular datasets lowers the requirement for training large designs from scratch, saving energy and computing resources. Second, the release of light-weight designs for mobile or real-time environments makes sure that the tools established are environmentally friendly and available. Furthermore, open-sourcing the developed framework and adding to collective platforms can enable continued improvement and adoption by the more comprehensive research community. These approaches promote not just environmental sustainability however likewise technical and scholastic sustainability by promoting inclusive, replicable, and scalable research practices.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

This research focused on the development and examination of deep learning-based models for multilingual authorship attribution using both English and Bangla text. The research study started with the manual collection of a well balanced dataset consisting of literary and non-fiction texts from 6 diverse authors. These texts were preprocessed through standardized NLP techniques, consisting of lowercasing, punctuation removal, stop word filtering, lemmatization, and tokenization utilizing multilingual tokenizers.

A range of artificial intelligence and deep knowing designs were implemented, ranging from classical methods like Logistic Regression and Random Forest to sophisticated deep learning architectures such as LSTM, BiLSTM with Attention, and CNN+LSTM. The research study's main contribution lies in the application and evaluation of transformer-based designs, particularly BERT (bert-base-multilingual-cased) and XLM-RoBERTa, for cross-lingual author detection.

Each model was evaluated using performance metrics such as accuracy, precision, recall, F1-score, Cohen's Kappa, and AUC-ROC. Among all, the proposed BERT model demonstrated the highest accuracy (95.5%) and attained ideal AUC scores for all authors, developing itself as the most reliable option in this study. The findings emphasize the transformative power of contextual embeddings in capturing stylistic nuances and linguistic diversity.

6.2 Conclusions

The experimental outcomes of this study plainly indicate that transformer-based architectures, particularly bert-base-multilingual-cased, deal exceptional performance in the task of multilingual author attribution. These designs excel at catching semantic, syntactic, and contextual features throughout varied text samples, surpassing both conventional maker finding out designs and earlier deep learning approaches. The success of the proposed BERT model demonstrates that authorial designs can be efficiently discovered and distinguished using deep contextual embeddings, even in complex multilingual settings. The model's high precision, stable learning habits, and robustness against stylistic overlap in between authors make it extremely suitable for real-world applications such as digital forensics, content confirmation, and anti-plagiarism systems.

In conclusion, this research study provides a scalable and precise framework for author detection, leading the way for future work in multilingual NLP. By leveraging transfer learning and contextualized embeddings, it is possible to significantly enhance the reliability and generalization of authorship attribution systems across languages and genres.

6.3 Limitations

Despite the high precision achieved by transformer-based models, this study has a number of limitations. The dataset is fairly small and restricted to six authors, which limits the generalizability of the outcomes to wider and more varied author swimming pools. The texts used are curated literary and non-fiction works, which might not reflect the intricacies of real-world data such as informal, noisy, or code-switched text frequently found on social networks or online platforms. Although multilingual designs like BERT and XLM-RoBERTa were used, the study does not deeply check out cross-lingual transferability or low-resource language situations. Another substantial constraint is the lack of interpretability in deep knowing designs, particularly transformer architectures, which work as black boxes and offer limited insight into their decision-making procedures. In addition, the computational needs of training and fine-tuning these big designs present scalability challenges and add to ecological concerns due to high energy usage. The effectiveness of the designs was not evaluated against adversarial inputs or texts designed to obscure composing design, leaving their effectiveness in forensic or deceptive contexts unsure.

6.4 Implication for Further Study

This research contributes substantially to the fields of natural language processing, forensic linguistics, and cyber forensics. Its useful implications extend to numerous domains including cybersecurity, education, law enforcement, and digital journalism. By enhancing the accuracy, generalizability, and effectiveness of authorship attribution designs, the research study lays the foundation for automated systems that can find stylistic signatures throughout several languages, categories, and platforms.Using pre-trained language models and tweak them on specific datasets reduces the requirement for training large designs from scratch, saving energy and computing resources. By enhancing the precision, generalizability, and effectiveness of authorship attribution designs, the research study lays the foundation for automated systems that can spot stylistic signatures across several languages, categories, and platforms.

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