AuthenWrite: An Intelligent Framework for Handwriting-Based Authorship Verification and Automated Academic Evaluation

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***Abstract*—The increasing volume of handwritten academic submissions in higher education has intensified the need for scalable, objective, and integrity-preserving evaluation systems. Traditional manual grading is time-consuming and prone to inconsistencies, while many automated grading systems fail to address handwritten authorship verification. To overcome these limitations, this work proposes AuthenWrite, an AI-driven framework that integrates handwriting authentication with automated content evaluation. A Siamese Convolutional Neural Network (CNN) is used to verify authorship by learning writer-specific handwriting features. Verified documents are then processed using Optical Character Recognition (OCR) to convert handwritten text into machine-readable form. The extracted content is semantically analyzed using Sentence-BERT embeddings and a vector-based retrieval mechanism. A retrieval-augmented Large Language Model (LLM) evaluates student responses against instructor-provided reference material. Finally, a weighted scoring mechanism combines handwriting confidence and semantic evaluation to generate final grades and feedback. The proposed system improves grading consistency, reduces instructor workload, and strengthens academic integrity.**

Index Terms—Handwriting Authentication, Siamese Neural Networks, Optical Character Recognition, Semantic Retrieval, Retrieval-Augmented Generation, Automated Grading

I. Introduction

The rapid expansion of student populations in modern educational institutions has significantly increased the complexity of evaluating handwritten academic work. As class sizes grow and the volume of assignments rises, instructors are required to process large numbers of submissions within limited timeframes. Conventional manual grading practices are therefore becoming increasingly unsustainable, as they are time-intensive, cognitively demanding, and inherently subjective. Variations in evaluator interpretation, fatigue, and time constraints can lead to inconsistencies in grading outcomes, potentially affecting fairness and reliability. Consequently, educational institutions are actively seeking scalable, efficient, and objective evaluation mechanisms that can maintain high assessment standards while reducing the workload placed on educators.

Beyond the challenge of grading efficiency, ensuring academic integrity remains a persistent concern in academic environments. Instances of proxy submissions, impersonation, and forged handwritten assignments can undermine the credibility of assessment processes and compromise fairness among students. While several automated grading systems have been developed to address large-scale evaluation needs, most existing solutions primarily focus on textual similarity analysis or plagiarism detection. These approaches, although useful for identifying copied content, do not verify whether the submitted handwriting genuinely belongs to the enrolled student. As a result, a critical security vulnerability remains unaddressed in many automated assessment frameworks.

To overcome these limitations, this study proposes an integrated evaluation framework that combines handwriting-based authorship verification with semantic answer assessment. The proposed system employs a Siamese Convolutional Neural Network (CNN) architecture to learn discriminative writer-specific feature representations and accurately distinguish genuine handwriting from potential forgeries. Once the authenticity of the submission is verified, handwritten responses are converted into machine-readable text using Optical Character

Recognition (OCR) technology. The extracted textual content is then processed through a Retrieval-Augmented Generation (RAG) pipeline, where transformer-based sentence embeddings and a Large Language Model (LLM) enable contextual understanding and evaluation of student responses against instructor-defined reference material. By integrating handwriting verification with advanced semantic evaluation techniques, the proposed framework delivers a comprehensive, end-to-end solution for scalable, reliable, and integrity-preserving automated assessment of handwritten assignments.

A. Problem Statement

Educational institutions face two major challenges in handwritten assignment evaluation: the inefficiency and inconsistency of manual grading, and the difficulty of detecting forged or proxy submissions. Existing automated evaluation tools typically address content assessment without validating handwriting authenticity. This separation creates a gap that compromises academic integrity. A comprehensive framework capable of jointly verifying handwriting authorship and performing semantically grounded content evaluation is therefore essential.

II. Literature Survey

The increasing instances of document forgery and proxy writing have prompted researchers to explore advanced solutions based on machine learning (ML) and deep learning (DL). Numerous studies have proposed approaches using Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Siamese Network architectures for handwriting verification, signature authentication, and writer recognition. These methods aim to extract distinctive handwriting features such as stroke pattern, curvature, slant, and spacing, which serve as unique identifiers of an individual's writing style. Earlier research primarily relied on handcrafted feature extraction methods such as texture analysis, histogram of oriented gradients (HOG), and geometrical stroke descriptors. While effective for small datasets, these methods lacked robustness when handling complex handwriting variations. With the advent of deep learning, models such as ResNet, VGGNet, and BiLSTM-based hybrid architectures have significantly improved the accuracy of handwriting classification and forgery detection. Modern systems also incorporate metric learning and contrastive loss functions to measure similarity between handwriting samples more precisely.

A. Learning Features for Offline Handwritten Signature Verification Using Spatial Transformer Network

Handwritten signatures are among the most enduring and trusted means of personal authentication, commonly used for legal, financial, and administrative verification. In modern biometric research, offline handwritten signature verification (OHSV) plays a critical role in identity authentication, particularly when dynamic writing features are unavailable. However, the challenge lies in distinguishing genuine signatures from skilled forgeries that often exhibit high visual similarity.

Early research on offline signature verification relied mainly on handcrafted feature extraction techniques such as geometric descriptors, stroke width analysis, and texture-based features. Methods such as Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) were widely used to detect local patterns in signatures. Although these techniques provided reasonable performance, they were highly sensitive to noise, variations in writing styles, and dataset diversity.

Experimental results demonstrate that the integration of Spatial Transformer Networks and Focal Loss significantly improves verification accuracy across multiple datasets. The model achieves high performance on datasets such as CEDAR, BHSig-Hindi, and BHSig-Bengali. These findings highlight the effectiveness of deep learning architectures in handling complex handwriting variations and improving signature ver- ification systems.

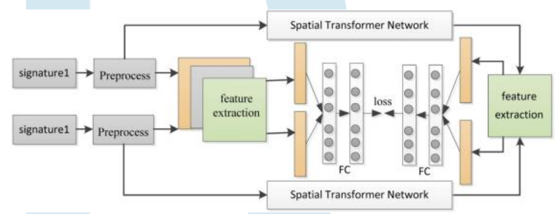

Fig. 1. The architecture of the proposed method

B. Using AI Explainable Models and Handwriting/Drawing Tasks for Psychological Well-Being

The increasing prevalence of mental health disorders such as depression, anxiety, and stress has encouraged researchers to explore innovative diagnostic approaches beyond traditional clinical methods. Conventional mental health assessments rely heavily on interviews and questionnaires, which may suffer from subjectivity and inconsistent reporting. Consequently, researchers have begun investigating behavioral biomarkers derived from handwriting and drawing tasks as potential indicators of psychological conditions.

Machine learning techniques have been increasingly applied to analyze handwriting-based behavioral data. Algorithms such as XGBoost, decision trees, and deep neural networks have demonstrated strong predictive performance in identifying patterns associated with mental health conditions. However, many machine learning models operate as "black boxes," making it difficult to understand how predictions are generated.

To address this limitation, researchers have introduced Explainable Artificial Intelligence (XAI) methods that provide transparency and interpretability in AI models. Explainable AI techniques enable researchers and clinicians to understand which features contribute most significantly to the model's predictions. One such approach is the Entropy-based Logic Explained Network (e-LEN), which integrates logical reasoning with neural learning mechanisms. Unlike traditional post-hoc explanation methods, e-LEN generates interpretable rule-based explanations directly from the model architecture. This design improves trust and transparency in AI-driven decision-making systems.

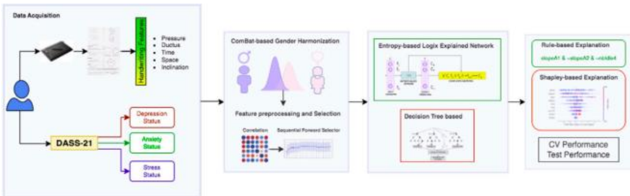

Fig. 2. Workflow of proposed method

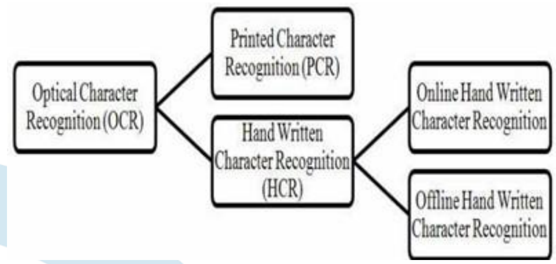

Fig. 3. Classification diagram

C. Deep Learning-Based Writer Identification Using Siamese Neural Networks

Handwriting verification and writer identification have gained significant attention in recent years due to their applications in document authentication, forensic analysis, and academic integrity systems. Traditional handwriting verification approaches relied mainly on handcrafted features such as stroke geometry, contour analysis, and texture descriptors. While these methods were useful in controlled environments, they often struggled to capture the complex variations in handwriting styles across different individuals.

To overcome these limitations, researchers have increasingly adopted deep learning-based approaches, particularly Siamese Neural Networks, for handwriting verification. A Siamese Neural Network consists of two identical neural networks that share the same architecture and parameters. These twin networks process two input images simultaneously and learn to measure the similarity between them. Instead of directly classifying handwriting samples, the model learns a feature representation that captures the unique characteristics of a writer's handwriting.

In this approach, each handwriting image is passed through convolutional layers that extract spatial features such as stroke curvature, spacing patterns, character structure, and writing orientation. The extracted features are then transformed into high-dimensional feature embeddings. The similarity between two embeddings is calculated using distance metrics such as Euclidean distance or cosine similarity. If the distance between the embeddings is small, the handwriting samples are considered to belong to the same writer; otherwise, they are classified as belonging to different writers.

III. METHODOLOGY

The proposed AuthenWrite system follows a systematic methodology that integrates artificial intelligence, deep learning, and computer vision techniques to verify the authenticity of handwritten academic submissions. The methodology is designed to capture both spatial and sequential characteristics of handwriting in order to accurately determine whether a submitted document belongs to the claimed writer. The overall workflow consists of multiple stages, including data collection, preprocessing, feature extraction, similarity learning, and verification.

A. Data Collection : Handwritten samples are collected from multiple individuals to create a reference dataset. These samples represent genuine handwriting patterns that will be used for comparison during the verification process. Collecting multiple samples from each writer helps capture natural variations in handwriting and improves the reliability of the model.

B. Image Acquisition : Handwritten assignments are captured using scanners, digital tablets, or mobile cameras. The images are stored in formats such as JPG or PNG with sufficient resolution to preserve handwriting details like stroke thickness and character structure.

C. Data Preprocessing : Preprocessing techniques such as grayscale conversion, noise removal, binarization, resizing, and deskewing are applied to improve image quality. These steps help remove background noise and standardize the input images for accurate analysis.

D. Image Segmentation : The preprocessed handwriting images are segmented into smaller components such as lines or words. Segmentation allows the system to focus on important handwriting structures and analyze them more effectively.

E. Feature Extraction using CNN : A Convolutional Neural Network (CNN) is used to extract spatial features from handwriting images. The model learns patterns such as stroke shapes, character spacing, and writing style directly from the images.

F. Sequential Pattern Learning using BiLSTM : The extracted features are passed to a Bidirectional Long Short-Term Memory (BiLSTM) network to analyze sequential writing patterns. This helps the system understand the flow and structure of handwriting.

G. Similarity Learning using Siamese Network : A Siamese Neural Network compares two handwriting samples and calculates a similarity score. This score indicates whether the samples belong to the same writer.

H. Classification and Result Generation : Based on the similarity score, the system classifies the handwriting as genuine or forged. The verification result is then displayed through a web interface, allowing educators to easily analyze handwriting authenticity.

IV. PROPOSED SYSTEM

TThe proposed system, AuthenWrite, is an AI-based handwriting verification framework designed to detect forged or proxy-written handwritten assignments and ensure academic integrity. Traditional manual verification methods are often time-consuming and prone to human error, especially when evaluating large numbers of submissions. To address this issue, the proposed system integrates computer vision and deep learning techniques to automatically analyze handwriting patterns and verify their authenticity. The system employs a hybrid deep learning architecture consisting of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN model extracts spatial features such as stroke patterns, character structure, spacing, and writing slant from handwriting images. These features are then processed by the BiLSTM network to capture the sequential flow and contextual relationships present in handwriting. To compare handwriting samples, a Siamese Neural Network is used. This network processes two handwriting samples simultaneously and generates feature embeddings for each sample. A similarity metric is then used to measure the relationship between the two embeddings. If the similarity score exceeds a predefined threshold, the handwriting samples are considered to belong to the same writer; otherwise, they are identified as potential forgeries. The system also includes an image preprocessing stage, where techniques such as grayscale conversion, noise removal, and resizing are applied to improve image quality and ensure accurate feature extraction. In addition, a web-based interface allows educators to upload handwritten assignments and obtain verification results efficiently. Overall, the AuthenWrite system provides an automated and reliable approach for handwriting authentication, helping educational institutions maintain transparency and fairness in academic evaluations.

V. Feasibility Study

A feasibility study evaluates whether the proposed AuthenWrite system can be successfully developed and implemented using available technologies and resources. It helps identify potential challenges and ensures that the system is practical for real-world use. The feasibility analysis mainly considers technical, operational, and economic aspects.

A. Technical Feasibility

Technical feasibility examines whether the required technologies and tools are available to implement the system. The AuthenWrite system utilizes widely used technologies such as Python, TensorFlow, OpenCV, and deep learning frameworks. Models like CNN, BiLSTM, and Siamese Neural Networks are used for handwriting analysis and verification. Since these technologies are well supported and accessible, the development and implementation of the system are technically feasible.

B. Operational Feasibility

Operational feasibility determines whether the system can be easily used by its intended users. The proposed system provides a simple web-based interface that allows teachers to upload handwritten assignments and receive verification results. This reduces the manual effort required for handwriting comparison and improves efficiency in academic evaluation.

C. Legal Feasibility

Legal feasibility ensures that the system complies with institutional and ethical standards. The AuthenWrite system analyzes handwriting samples only for academic verification purposes and does not misuse personal data. Proper data handling practices can be implemented to maintain privacy and security.

D. Economic Feasibility

Economic feasibility evaluates the cost of developing and maintaining the system. The AuthenWrite system is built using open-source libraries and cloud platforms, which signifi- cantly reduce development costs. Additionally, the automation of handwriting verification reduces administrative workload, making the system cost-effective.

E. Social Feasability

Social feasibility considers how the system benefits users and society. The system promotes academic honesty and fairness by detecting forged or proxy-written assignments. It helps educational institutions maintain transparency and integrity in the evaluation process.

VI. PROPOSED SYSTEM DESIGN

The proposed system design for AuthenWrite integrates deep learning models, image processing techniques, and a web-based interface to verify the authenticity of handwritten academic submissions. The system is designed to analyze handwriting characteristics and compare them with stored reference samples in order to determine whether a document belongs to the claimed writer. The overall architecture consists of multiple stages including data input, preprocessing, feature extraction, similarity analysis, and result generation. These stages work together to ensure accurate and reliable handwriting verification.

The process begins when a user uploads a handwritten doc- ument through the web-based interface. The documents may be captured using scanners, mobile cameras, or digital writing devices and are stored as image files such as JPG or PNG. These images serve as the input for the verification system. Once the image is uploaded, it undergoes several preprocessing operations to improve image quality and standardize the data for further analysis.

During preprocessing, techniques such as grayscale conver- sion, noise removal, binarization, resizing, and normalization are applied to the handwriting images. These operations help remove background noise, improve contrast, and separate handwriting strokes from the background. Preprocessing ensures that the input images are clean and consistent, which improves the performance of the machine learning models used for handwriting analysis.

After preprocessing, the system performs feature extraction using Convolutional Neural Networks (CNN). The CNN model analyzes the handwriting images and automatically learns spatial features such as stroke patterns, character shapes, writing slant, and spacing between letters. These features represent the visual characteristics that distinguish one person's handwriting from another.

The extracted features are then passed to a Bidirectional Long Short-Term Memory (BiLSTM) network, which analyzes sequential patterns in handwriting. BiLSTM processes the data in both forward and backward directions, allowing the system to capture contextual relationships and writing flow. This step helps the model understand the dynamic structure of handwriting more effectively.

To verify handwriting authenticity, the system uses a Siamese Neural Network that compares two handwriting samples. The network generates feature embeddings for each sample and calculates a similarity score using distance metrics. If the similarity score exceeds a predefined threshold, the handwriting is considered genuine; otherwise, it is classified as a potential forgery.

Finally, the verification result is displayed through the web interface, where educators can view similarity scores and authenticity predictions. This automated system helps detect proxy-written assignments and supports maintaining fairness and transparency in academic evaluations.

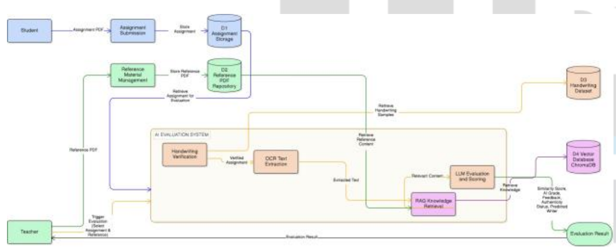

Fig. 4. Architecture diagram

VII. RESULT

The proposed AuthenWrite system was implemented and evaluated to examine its effectiveness in verifying the authenticity of handwritten academic submissions. The system processes uploaded handwriting samples through multiple stages including preprocessing, feature extraction, sequential analysis, and similarity comparison. The preprocessing stage successfully enhanced the quality of handwriting images by applying techniques such as grayscale conversion, noise removal, resizing, and normalization. These operations helped remove unwanted background noise and improved the clarity of handwriting strokes, allowing the system to analyze the images more accurately.

The Convolutional Neural Network (CNN) model effectively extracted spatial features from handwriting images. These features included stroke shapes, character structure, writing slant, and spacing between letters, which represent the visual characteristics of an individual's handwriting style. By learning these patterns automatically from the dataset, the CNN model was able to identify unique handwriting traits that distinguish one writer from another.

Following feature extraction, the Bidirectional Long Short-Term Memory (BiLSTM) network analyzed the sequential patterns present in the handwriting samples. The BiLSTM model processes the data in both forward and backward directions, allowing the system to understand the contextual relationships and writing flow between characters. This sequential analysis improved the system's ability to capture dynamic writing behavior and enhanced the overall accuracy of handwriting verification.

To determine the authenticity of handwriting samples, the system utilized a Siamese Neural Network architecture. This network compared two handwriting samples by generating feature embeddings for each sample and calculating a similarity score using distance metrics. The similarity score represented the degree of similarity between the handwriting patterns. When the similarity score exceeded a predefined threshold, the handwriting samples were classified as belonging to the same writer; otherwise, the system identified the handwriting as a potential forgery.

The verification results were displayed through a web-based interface, which allowed users to upload handwritten assignments and obtain authentication results quickly. The interface presented similarity scores and classification outcomes, enabling educators to easily evaluate handwriting authenticity. The automated nature of the system reduced manual effort and minimized subjective errors that often occur during manual handwriting comparison.

Overall, the results demonstrated that the proposed AuthenWrite system is capable of effectively analyzing handwriting patterns and identifying inconsistencies in writing styles. The integration of CNN, BiLSTM, and Siamese Neural Networks provided a reliable approach for handwriting verification. The system offers a practical solution for detecting proxy-written assignments and helps educational institutions maintain transparency, fairness, and academic integrity in student evaluations.

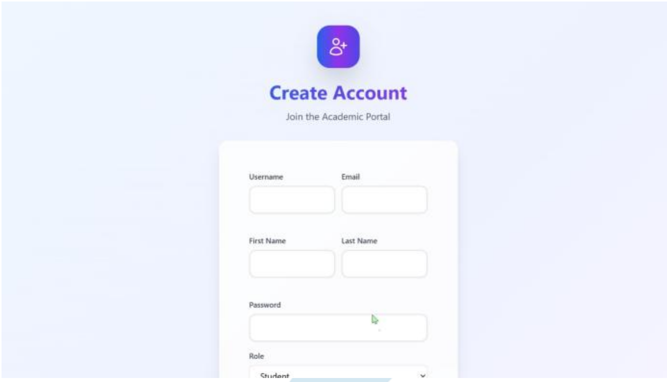

Fig. 5. LOGIN INTERFACE

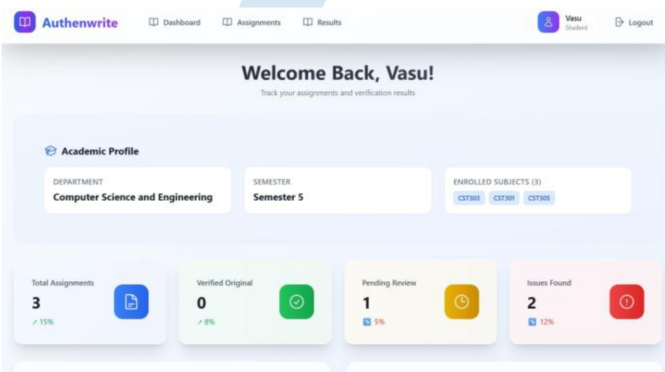

Fig. 6. USER DASHBOARD

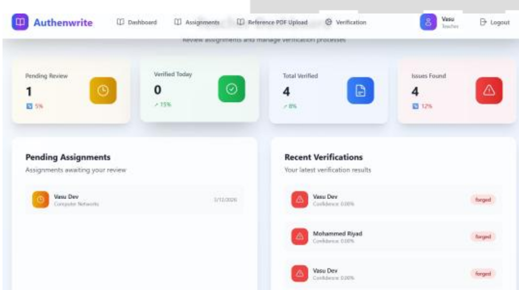

Fig. 7. ADMIN DASHBOARD

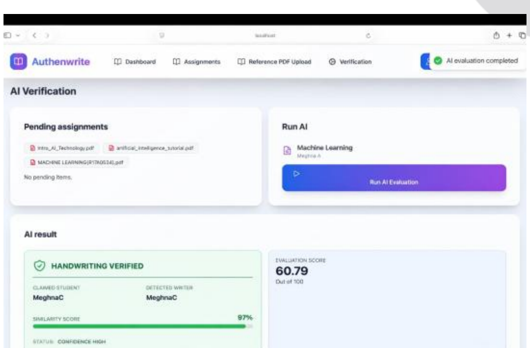

Fig. 8. RESULT(AUTHENTIC)

VIII. CONCLUSION

The proposed AuthenWrite system provides an effective solution for verifying the authenticity of handwritten academic submissions using artificial intelligence and deep learning techniques. By integrating CNN, BiLSTM, and Siamese Neural Networks, the system analyzes handwriting patterns and compares samples to determine whether they belong to the same writer. The preprocessing stage improves the quality of handwriting images, while the deep learning models extract spatial and sequential features for accurate verification. The web-based interface allows educators to upload handwritten assignments and obtain verification results quickly. Overall, the AuthenWrite system offers an automated and reliable approach for handwriting authentication, helping educational institutions maintain fairness and academic integrity in student evaluations.

IX. FUTURE SCOPE

The proposed AuthenWrite system can be further improved by incorporating advanced deep learning models and larger handwriting datasets to enhance verification accuracy. Future developments may include the integration of transformer-based architectures and attention mechanisms to better capture complex handwriting patterns.

The system can also be expanded to support multilingual handwriting analysis, allowing it to work with different scripts and languages. In addition, the integration of mobile applications or digital pen devices can enable real-time handwriting verification.

Future versions of the system may also incorporate explainable AI techniques to provide clearer insights into how handwriting verification decisions are made. These improvements will make the system more scalable and suitable for broader applications such as document authentication, signature verification, and forensic handwriting analysis.

REFERENCES

[1] S. Huang, W. Fu, Z. Zhang, and S. Liu, "Global-local fusion based on adversarial sample generation for image-text matching," *Information Fusion*, vol. 103, p. 102084, 2024.

[2] T. Hasan, M. A. Rahim, J. Shin, S. Nishimura, and M. N. Hossain, "Dynamics of digital pen-tablet: Handwriting analysis for person identification using machine and deep learning techniques," *IEEE Access*, vol. 12, pp. 8154–8177, 2024.

[3] A. Mezghani, M. Elleuch, and M. Kherallah, "DL vs. traditional ML algorithms to recognize Arabic handwriting script: a review," in *Intelligent Systems Design and Applications*. Springer, 2023, pp. 404–414.

[4] I. Aouraghe, G. Khaissidi, and M. Mrabti, "A literature review of online handwriting analysis to detect Parkinson's disease at an early stage," *Multimedia Tools and Applications*, vol. 82, no. 8, pp. 11923–11948, 2023.

[5] S. Liu, T. H. He, J. Y. Li, Y. T. Li, and A. Kumar, "An effective learning evaluation method based on text data with real-time attribution: A case study for mathematical class with students of junior middle school in China," *ACM Transactions on Asian and Low-Resource Language Information Processing*, vol. 22, no. 3, pp. 1–22, 2023.

[6] J. Shin et al., "Identifying ADHD for children with coexisting ASD from fNIRs signals using deep learning approach," *IEEE Access*, vol. 11, pp. 82794–82801, 2023.

[7] M. Mendez, M. G. Merayo, and M. Nunez, "Long-term traffic flow forecasting using a hybrid CNN-BiLSTM model," *Engineering Applications of Artificial Intelligence*, vol. 121, p. 106041, 2023.

[8] M. M. Taye, "Theoretical understanding of convolutional neural network: concepts, architectures, applications, future directions," *Computation*, vol. 11, no. 3, p. 52, 2023.

[9] K. Chaudhari and A. Thakkar, "Survey on handwriting-based personality trait identification," *Expert Systems with Applications*, vol. 124, pp. 18–30, 2019.

[10] M. Prinzi, A. Rizzo, and F. Ferraro, "Explainable artificial intelligence for behavioral handwriting analysis in psychological assessment," *Artificial Intelligence in Medicine*, vol. 140, pp. 102524, 2024.

[11] J. Johnson, C. Li, and M. Rabinovic, "Adjusting batch effects in microarray expression data using empirical Bayes methods," *Biostatistics*, vol. 8, no. 1, pp. 118–127, 2006.

[12] A. Graves, S. Ferna´ndez, F. Gomez, and J. Schmidhuber, "Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks," *Proceedings of the 23rd International Conference on Machine Learning*, pp. 369–376, 2006.

[13] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *International Conference on Learning Representations (ICLR)*, 2015.

[14] A. Vaswani et al., "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[15] T. Brown et al., "Language models are few-shot learners," *Advances in Neural Information Processing Systems*, vol. 33, pp. 1877–1901, 2020.