

Comparative Evaluation of AI Tools in Signature Analysis - Forensic Approach to Authorship Identification

Ms. Vamshi S Kotian¹, Dr Saritha D'souza²

¹ *Research Guide, School of Social Work, Mangaluru*

² *Head, Pg Dept. Criminology and Forensic Science School of Social Work, Mangaluru*

I. INTRODUCTION

The concept of signature started long ago when people used symbols, seals or marks to represent their identity or show something belonging to them. Later, people started to write their names by hand as a signature.

According to Stephen Mason, before people wrote their names, they used different methods to prove their identity and agreements.

In the Medieval period, people were not able to read, write so handwritten signatures were not practiced. Instead of handwritten signatures marks, seals, objects, witnesses were used. Seals were used most commonly to represent authority and identity. To show approvals Kings pressed wax seals to the documents. Seals were trusted and people relied more on seals as there were limited literacy. Witnesses were also present as they were used to confirm that person has agreed to the contents of the documents.

Later on slowly these methods developed into an idea of personal signatures.

As literacy increased, the concept of manuscript signatures or handwritten signatures started evolving and they became common. People started using their names as their identity and to show consent. This was practiced usually in legal and commercial documents. However, signatures did not exist in similar form. As people were not able to write their full names they used shortened forms, initials, marks. Courts gradually accepted these signatures as valid signatures.

Mason explains that judges accepted different kinds of signatures, instead of forcing everyone to use only one style of signatures. So the signatures became common

to be used in legal documents like contracts, wills, property papers and bank documents. He also says that the purpose of signatures is not to show how beautiful the handwriting is, but to prove the identity and agreements.

Stephen Mason further explains that signatures evolved in many different forms depending upon the social conditions and legal needs. Some individuals used their surnames, fingerprints, symbols as their signatures. In several cases. Incomplete or unusual signatures were also accepted by courts if there was evidence of intention. The law focused more into the authentication rather than the appearance of signatures.

With the development of technology, signature evolved beyond handwriting. Rubber stamps, typewritten names, telegram confirmation, facsimile signatures began to be accepted in law and also in businesses. The judges explain that technology will change over time but the main function of signature remains the same to confirm the consent and to identify the individual.

Stephen Mason explains that the latest technology of using electronic signatures is the old idea of authentication and it is just a modern development. He says throughout history people made so many methods to show their identity and consent. Electronic signatures are another step of evolution.

He argues that law should not only focus on the old traditional handwritten signatures because technology changes over time and it keeps on developing. Instead what actually matters the most is that whatever the methods are used, does it show personal identity and

the intention of the agreement or consent or to approve a document.

Mason explains that electronic signatures can be used and accepted the same way as handwritten signatures if it proves identity and has a clear authentication. He notes that the courts gradually accept the electronic signatures and its methods as there is rapid development in technology as well as businesses and communication increasingly moved to computers and the internet.

A signature is a personal mark or written representation of a person's name used to show identity, approval, consent or authentication of a document.

It is the most common method used to confirm the ownership, responsibility or consent. A signature is a form of handwriting which appears in any form like initials, seal, shortened names, marks, electronic signatures.

Although signature is commonly associated with handwriting today, the concept of signature has existed for thousands of years ago in many different forms.

The history of signatures can be traced back to ancient civilizations such as Greece, Mesopotamia, Rome and Egypt where people used carved symbols, seals and personal marks to identification and approvals. Kings, merchants and Government Officials used engraved stamps on clay tablets or wax seals on important documents to represent their ownership or authority.

In Modern period, Signatures became commonly used in Government, Businesses, Education, Banking etc. They are used in passports, checks, contracts, legal records and in application forms. Now a days electronic signatures are widely used and accepted for digital agreements, online transactions etc. These modern signatures use encryptions and security systems to prevent fraud related issues.

Albert S Osborn, one of the pioneers of Forensic Document Examination discussed the scientific study of signatures and questioned documents in his famous book Questioned Documents. According to Albert, a questioned document is any document whose authenticity, origin or authorship is disputed. This may include forged documents, anonymous letters, erased writings, counterfeit documents etc.

He also explained that every person will develop a natural writing habits through a repeat of practices over many years. So as a result there will be a individual characteristics in every genuine signatures which is unique and has a individuality. These individual characteristics include pen pressure, speed, alignment, spacing, connecting strokes etc. Even when a person tries to change their handwriting certain natural habits will remain same. Because of this, signatures can be scientifically examined to determine whether genuine or forged.

He also described the importance of comparing genuine and disputed signatures. He stated that one should not come to a conclusion just by observing one writing sample. Instead several genuine writing samples should be collected and analyzed. He emphasized the use of photography, microscopes, magnification and detailed examination techniques to study the characteristics of handwriting accurately. According to Albert Osborn, scientific methods will help investigators and also court to discover truth in disputed document cases.

The study of signatures is not only crucial in criminal cases but also in civil related cases and commercial matters. Forged signature are used in fraud investigations, banking crimes, fake wills, identity theft etc. Therefore, in Forensic Science signature examination became a most essential branch. Osborn believed that courts should give judgement based on Experts observation, analysis than the mere personal judgement.

Modern technologies have developed where the field of signature examination has been expanded. Along with the handwritten signatures experts now examine scanned signatures, photocopied signatures, electronic signatures. However, the main purpose of signature will remain the same - to identify person and confirm authentication or consent. Thus the concept of signature plays a major role in law, administration and Forensic Science.

II. REVIEW OF LITERATURE

A literature review is a concise summary and critical analysis of previous studies on a specific topic. It helps the researcher understand existing knowledge, identify areas that need more research, and establish a solid

foundation for the current study. Research Methodology: Methods and Techniques explains that this process involves examining past research to avoid repeating work and to guide the direction of the current study. According to Research Methodology: A Step-by-Step Guide for Beginners, a literature review is important for setting clear research objectives and understanding how the study can be applied in real-world situations.

A study conducted by Nemi Chandra Rathore, Akshay Juneja, Neeraj Kumar, Vijay Kumar, and Arvind Dhaka (2026), titled “A Hybrid Machine Learning Framework for Offline Signature Verification using Gray Wolf Optimization,” introduces an advanced system for verifying signatures called SignGuard. This research uses Principal Orientation Alignment (POA) to handle rotation issues and Gray Wolf Optimization (GWO) for preprocessing. It combines hybrid classifiers such as Support Vector Machine and XGBoost with texture features like CS-LBP and OC-CSLBP. The model achieved high accuracy, up to 98.77%, when tested on datasets including CEDAR, SID, BHSig260, and DeepSign Vault. The results show improved reliability and performance for practical applications in signature verification.

A study conducted by Janhavi Kadam, Gauri Phadtare, Ashwini Pawar, and Kamalkishor Maniyar (2025), titled “Offline Signature Verification Using Siamese Neural *Network*,” focuses on the challenge of distinguishing real from fake signatures in offline settings.

The study suggests a writer-independent system that compares signature images by calculating the Euclidean distance between them using a Siamese neural network. Since the model uses one-shot learning, it performs well with limited training data. The system achieved accuracy rates of 82% and 84% when tested on the BHSig260 datasets (Bengali and Hindi). The results show the model's ability to effectively identify genuine and counterfeit signatures, making it suitable for real-world use.

A study conducted by Abdullahi Ahmed Abdirahma, Abdirahman Osman Hashi, Mohamed Abdirahman Elmi, and Octavio Ernest Romo Rodriguez (2024) titled “Advancing Handwritten Signature Verification Through Deep Learning: A Comprehensive Study and

High-Precision Approach” focuses on improving offline signature verification using advanced deep learning models.

The study emphasizes how difficult it is to reliably discern between real and fake signatures. The authors use a variety of deep learning architectures, including MobileNet, ResNet50, InceptionV3, and VGG19, along with YOLOv5 for feature extraction and classification, to address this. Several benchmark datasets, such as Kaggle Signature, CEDAR, ICDAR, and SigComp, were used to test the model. The outcomes showed excellent performance across several datasets and high accuracy (around 89.8%). The paper suggests that merging multiple deep learning models boosts precision and dependability, making the approach acceptable for real-world signature verification applications.

A study conducted by Longcheng Ji, Hong Wang, Junxu Hou, Zhouping Chen, and Ziyang Li (2023), titled “Signature Authenticity Verification using a Cross-Path Four-Stream Network for Preventing Disguising Frauds,” introduces a new deep learning method to enhance the accuracy of signature verification. To improve the learning of features, the study proposes a Cross-Path Four-Stream Network (CPFN) that analyzes both original and inverted gray images using shared branches and a Cross-Path Attention module. The model showed low computational complexity and achieved high accuracy rates up to 100% when tested on the NUHSD, CEDAR, BHSig-B, and BHSig-H datasets. These results show how effectively the approach can identify fake signatures and prevent fraud.

A study conducted by Zihan Zeng and Jing Tian (2023), titled “Deep Learning Methods for Signature Verification,” explores various deep learning architectures for the purpose of signature verification. The paper presents models including CNN, RNN, and a hybrid CNN-RNN technique to enhance feature representation. In order to better distinguish between genuine and fraudulent signatures, the study further improves Path Signature Features by incorporating temporal information. The results suggest that these proposed models effectively improve the performance of signature verification.

A study conducted by Sounak Dey, Anjan Dutta, J. Ignacio Toledo, Suman K. Ghosh, Josep Lladós, and Umapada Pal (2023), titled “SigNet: Convolutional Siamese Network for Writer Independent Offline Signature Verification,” proposes a deep learning approach using a Siamese network for signature verification. By minimizing the distance between authentic signature pairs and maximizing it for fraudulent ones, the model learns how similar features are. When evaluated on several benchmark datasets, the system performed better than current techniques. The results illustrate the efficiency of Siamese networks in handling writer-independent signature verification across different languages and writing styles.

A study by Deniz Engin, Alperen Kantarcı, Seçil Arslan, and Hazım Kemal Ekenel (2023), titled “Offline Signature Verification on Real-World Documents,” focuses on the challenges of verifying signatures in real-world scenarios where documents contain noise such as stamps, seals, and occlusions. The study suggests a technique that combines CNN-based feature extraction with CycleGAN for stamp removal. After preprocessing, the model performed better on both the Tobacco-800 dataset and a new dataset. The findings show how difficult it is to verify signatures in real-world situations and how important it is to manage document noise for greater accuracy.

A study conducted by E.N. Zois, D. Tsourounis, I. Theodorakopoulos, A.L. Kesidis, and G. Economou (2023), titled “A Comprehensive Study of Sparse Representation Techniques for Offline Signature Verification,” focuses on improving signature verification using sparse representation methods. The study investigates preprocessing methods, dictionary size, sparsity level, and feature extraction methodologies. To improve feature representation, it introduces spatial pyramid segmentation and second-order statistics. The model achieved state-of-the-art performance when tested on datasets like CEDAR, MCYT-75, GPDS, and UTSIG. The findings demonstrate how sparse representation can improve verification accuracy even when using a small number of training samples.

A study conducted by **Dr.R.N.Devendra Kumar**, Jasswanth M, Gokulraj G, Dharani Dharan A, and

Enba Prabhu M (2023), titled “Signature Verification Using Convolutional Neural Network,” focuses on improving the accuracy and efficiency of signature verification systems. The study highlights the need for automated solutions due to the time-consuming and error-prone nature of traditional methods. The authors suggest a Convolutional Neural Network (CNN)-based model that uses deep learning to assess and validate handwritten signatures. The system’s integration with a Streamlit interface makes real-time and user-friendly signature verification possible. The proposed strategy improves accuracy and efficiency compared to current methods. According to the study’s findings, CNN-based systems offer a dependable and effective way to automate signature verification in modern digital applications.

A study conducted by Wanghui Xiao and Yuting Ding (2022), titled “A Two-Stage Siamese Network Model for Offline Handwritten Signature Verification,” focuses on improving offline signature verification using deep learning.

The study points out that typical Siamese networks struggle with unbalanced datasets and accurately capturing writing styles. The authors suggest using Focal Loss to manage data imbalance and a two-stage Siamese network that evaluates both original and enhanced signature images. When tested on four different signature datasets, the model outperformed other approaches. It was also successfully applied to a real-world Chinese signature collection. The study concludes that the suggested model is useful for biometric authentication as it improves accuracy and reliability in identifying real and fake signatures.

A study conducted by Merve Varol (2021) titled “Signature Verification Using Siamese Neural Network One-Shot Learning” focuses on improving offline signature verification using biometric techniques. The study highlights that the absence of dynamic elements makes offline signature verification more challenging compared to online methods. To overcome the issue of needing large datasets, the author proposes using a Siamese Neural Network combined with One-Shot Learning. This approach allows for accurate classification even when the number of signature samples is limited. The model was tested using several datasets, including 4NSigComp2012, SigComp2011, 4NSigComp2010,

and BHsig260. The results showed that the proposed method is effective, achieving high verification accuracy ranging from 89% to 93%. According to the study's findings, using Siamese networks with One-Shot Learning is a reliable approach for offline signature verification, particularly when data is limited.

A study by Anamika Jain, Satish Kumar Singh, and Krishna Pratap Singh (2021) titled "Signature Verification using Geometrical Features and Artificial Neural Network Classifier" focuses on signature verification based on the geometrical characteristics of signature images. The study uses an Artificial Neural Network (ANN) classifier after extracting features such as center, isolated points, and connected components. The approach achieved a lower Equal Error Rate (EER) and higher accuracy when tested on the MCYT and BHSig260 datasets. The findings indicate that geometrical feature-based methods, when combined with ANN, can effectively validate signatures even with limited texture information.

A study conducted by Dimitrios Tsourounis, Ilias Theodorakopoulos, Elias N. Zois, and George Economou (2021) titled "From Text to Signatures: Knowledge Transfer for Efficient Deep Feature Learning in Offline Signature Verification" focuses on improving feature learning in offline signature verification using deep learning. The work introduces a transfer learning strategy where a Convolutional Neural Network (CNN) is first trained on handwritten text for writer identification and then modified to use metric learning with contrastive loss for signature verification. When evaluated on the CEDAR, MCYT-75, and GPDS300GRAY datasets, the system produced results comparable to state-of-the-art techniques but with significantly less training data. The results demonstrate the effectiveness of knowledge transfer in enhancing the accuracy of signature verification.

A study by Mervae (2021) titled "A Comprehensive Study on Offline Signature Verification" provides an overview of various techniques used in offline signature verification.

The paper discusses the evolution from traditional handmade feature-based methods to modern deep learning algorithms. It highlights important challenges such as forgery detection, signature variability, and the

lack of dynamic information. The study concludes that while deep learning has improved accuracy, signature verification systems still need further improvements. The development and performance of machine learning and deep learning models, such as Convolutional Neural Networks (CNNs), Siamese Networks, and architectures like Res Net and VGG, are the main goals of most current research on offline handwritten signature verification.

These studies frequently use standardized datasets and statistical performance criteria like accuracy and error rates. However, in the context of forensic application, these methods have significant drawbacks. First of all, they place a strong emphasis on computing efficiency without considering whether the analysis and findings are consistent with accepted forensic document inspection criteria, which are crucial for legal validity. Second, most research concentrates on individual models rather than doing a comparative analysis of various AI platforms, especially contemporary AI-based technologies. Thirdly, little study has been done on the dependability and consistency of AI results when the same set of signatures is examined repeatedly—a crucial prerequisite for forensic investigations.

Additionally, with the rise of sophisticated AI platforms like Gemini, DeepSeek, Microsoft Copilot and Claude AI, there hasn't been a thorough assessment of their capacity for signature analysis, particularly with regard to interpretation, explanation, and forensic applicability.

Therefore, an obvious gap remains in evaluating AI tools from a forensic perspective, notably considering intra-tool consistency, inter-tool variability, and adherence to forensic handwriting standards. By offering a comparative assessment of several AI platforms in signature analysis for authorship identification, the current study seeks to close this gap between forensic dependability and technical innovation.

III. METHODOLOGY

This part of the study describes the methodology adopted to carry out the research in a systematic and

scientific manner. It outlines the overall research design, methods of data collection, sampling techniques, and tools used for analysis. The study follows an appropriate research approach to ensure accuracy and reliability of results. Data were collected from relevant sources and analyzed using suitable techniques to meet the objectives of the research. The methodology also justifies the selection of methods and procedures, ensuring that the study can be replicated and validated. According to C. R. Kothari, research methodology is a systematic way to solve the research problem, which guides the entire research process.

3.1 NEED FOR THE STUDY

As artificial intelligence (AI) is being used more and more in now a days, it is important to check how reliable it really is, especially in signature analysis. Traditional handwriting examination depends on expert knowledge and proven methods, while AI tools are being used quickly without proper testing. So, this study is needed to find out how accurate and consistent these AI tools are, and whether they are useful in real forensic work. It will also compare different AI tools to see how they perform.

The results of this study will help us understand if AI can be trusted to identify who wrote a signature, and also point out its limitations in forensic practice.

3.2 AIM OF THE STUDY

The aim of the study is to check the accuracy of 4 AI tools, that can detect the genuine signature and simulated forgery signature using forensic approach.

3.3 OBJECTIVES OF THE STUDY

- To evaluate the consistency of AI results while analyzing the same set of signatures repeatedly.
- To evaluate the ability of AI systems to analyze signatures based on traditional forensic handwriting principles.
- To assess the consistency of results produced by various AI platforms while analyzing the same set of signatures.

3.4 RESEARCH QUESTION

- Do AI tools give consistent results when the same set of signatures is analyzed repeatedly?

- Can AI tools analyze signature same as the way of Forensic Experts?
- Do Different AI tools give the same results when the same set of signatures is given?

3.5 RESEARCH DESIGN

The study adopts an Experimental Research design. A quantitative approach with qualitative interpretation will be used. Signature samples, including genuine and simulated forged, will be collected and analyzed. Multiple AI tools will assess the same set of signatures repeatedly to evaluate the consistency, while comparisons across tools will determine tool variability and adherence to forensic handwriting principles. The results will be recorded and analyzed to assess the reliability and forensic applicability of AI-based signature analysis.

3.6 UNIVERSE AND SAMPLE SIZE

For the purposes of study, Adults in Mangaluru City were selected as the Universe. A total number of 10 samples are taken from the respondents. The sampling technique used is Non-probability Snowball technique.

3.7 TOOLS OF DATA COLLECTION

The instruments used in this study include handwritten signature samples (both genuine and simulated forged), cardboard with [A4] White sheet, for collecting the signature and artificial intelligence tools such as Gemini AI, Microsoft Copilot, Claude AI and Deep seek AI for the analysis. Standard forensic document examination principles are also followed to compare and evaluate the signatures.

3.8 PROCEDURE

Prior to sample collection, informed consent will be obtained from all participants after explaining the purpose of the study, and each participant signed a consent form. The participants will be then seated comfortably in a relaxed position. A cardboard support with an A4 sheet placed on it will be provided to ensure a uniform writing surface, and a ball pen will be given to each participant for signing. Participants will be instructed to provide their admitted (genuine) signature samples under normal writing conditions. Subsequently, a different participant will be asked to imitate and forge the signature of the original signer,

thereby generating simulated forged signature samples for comparative analysis.

3.9 INCLUSION CRITERIA

Participants who are willing to participate and provide informed consent are included in the study. Individuals capable of giving clear and stable signature samples under normal writing conditions are considered. Only those participants who can provide both genuine (admitted) signatures and allow their signatures to be used for forgery simulation are included. Healthy individuals without any physical or neurological impairment affecting handwriting are selected.

3.10 EXCLUSION CRITERIA

Participants who do not provide informed consent or are unwilling to participate are excluded from the study. Individuals with conditions affecting handwriting, such as tremors, injuries, or neurological disorders, are not included. Signatures that are incomplete, or not provided under standardized conditions are excluded. Participants who fail to follow the instructions during signature collection are also excluded.

3.11 DATA ANALYSIS AND INTERPRETATION

The data given by different AI tools are checked and compared whether they give similar results as the way of a forensic expert. Then the same set of signatures will also be analyzed repeatedly to see whether the results are consistent. The results given by different AI tools are also checked and compared to see whether they give similar answers.

Then results are explained to understand which AI gives a similar interpretation as forensic experts and also which AI tools are more accurate and reliable.

3.12 REPORT DESIGN

Report design is the structured format used to present the research work in a clear and systematic manner. It refers to the systematic planning, organization, and presentation of information in a report such that the content becomes clear, logical, readable, and visually effective. It includes selecting the structure, format, layout, style, and sequence of the report so that the reader can clearly understand the purpose and also the findings and conclusions of the study or investigation. The major chapters in the report will be:

Chapter I: Introduction

Report design introduction is the first part of a report that presents background information about the subject, clarifies the aim of the research, and outlines the contents of the report to the reader. It aids the reader in grasping the setting, goals, and significance of the research.

Chapter II: Review of literature

This is a section of a research report in which prior studies, books, articles, and publications associated with the research problem are reviewed, analyzed, and summarized. This section will assist the researcher to understand the existing body of knowledge, find the gaps that existed in prior research, and build the base for the current study.

Chapter III: Methodology

The methodology is the specific procedure, ways and means which are employed by the researchers for gathering, analyzing and evaluating the data collected from the research and it illustrates how research was performed to meet research objectives.

Chapter IV: Data analysis and interpretation

It refers to arranging, looking over and providing an explanation of gathered data in order to interpret its meaning and derive results based upon the study objectives. Data analysis makes use of analytical or statistical techniques while interpretation provides explanation.

Chapter V: Major findings, suggestions and conclusions

Major findings refer to the key outcome or main observation from the study carried out upon evaluation of the data obtained. It is in relation with the study aims, the study objectives and key outcome of the research carried out.

The suggestions based on the findings in the study can be used to provide recommendations for improvement or further study and to offer suggestions to provide benefits for the society and in relation to application of the research to solve the current or the upcoming problems in the society.

Conclusion, refers to the end result, summarizing briefly the research carried out in study along with its

key findings and end result in an efficient and concise manner.

3.13 LIMITATIONS

1. Signatures were forged by people during study sessions, so these situations might be different from those real-life forgeries of high-expertise that are encountered in forensic casework.
2. This research was carried out with a very small group of 10 people only, which probably can't stand for a wider population.
3. Certain AI platforms, like Google Gemini, Microsoft Copilot, Claude, and DeepSeek, were the ones used for the study, and one can expect different results with other AI instruments.

IV. DATA ANALYSIS AND INTERPRETATION

Data analysis and interpretation are systematic processes used by researchers to categorize, sort, tabulate, and analyze collected data to discover trends and connections that will answer the research question. Through statistical and/or analytic techniques, data can be made easier to understand and summed up; when the results of an analysis are explained in terms

of the meaning and significance of the findings, this is referred to as data interpretation.

The AI signature analyses were qualitatively evaluated based on three parameters. These three parameters are Consistency Score (CS), Forensic Principle Adherence (FPA), and Authorship Discrimination Accuracy (ADA). Each parameter was interpreted descriptively to create a basic framework for assessing the performance of different AI platforms in the forensic analysis of signature.

In this study, the same set of 10 signature samples was given to each AI system - Gemini, Microsoft Copilot, Claude AI, and DeepSeek. Each sample was given two times with exactly the same prompts so that the changes in the response could be observed. The prompt given to each AI tools is as follows;

“Compare the set of signatures provided based on the handwriting characteristics observed by document expert to state whether all signatures are made by the same person.”

Further the examiner conducted a qualitative evaluation of the responses using the interpretations given in the table below as a guide.

4.1: Tabular Representation of Qualitative Interpretations Used for Analysis

Interpretation	Description
No Analysis	Complete failure to evaluate the signature
No Reference to Forensic Handwriting Principle	AI response does not mention any recognized forensic handwriting examination principle
Some Forensic Handwriting Principle Identified	AI response partially references two or six forensic handwriting principles
Poor Consistency	AI produces correct analysis in less than half of the repeated submissions of the same signature, indicating unstable and unreliable response behaviour
Good Consistency	AI produces correct analysis in majority of the repeated submissions of the same signature, indicating stable and reliable response behaviour
Poor Authorship Identification	AI correctly identifies the authorship of the signature in less than half of the repeated submissions, indicating inaccurate and

	inconsistent
Good Authorship Identification	AI correctly identifies the authorship of the signature in majority of the repeated submissions, indicating accurate and consistent determination

Table 4.1.01: Qualitative Analysis of Signature Samples using Gemini AI

Sample	CS	FPA	ADA
S-1	Good Consistency	Some Forensic Handwriting Principle	Good Authorship Identification
S-2	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-3	Poor Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-4	Poor Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-5	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-6	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-7	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-8	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-9	Good Consistency	Some Forensic Handwriting	Poor Authorship Identification

		Principle Identified	
S-10	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification

The data shown in Table 4.1.01, with regard to the Qualitative Analysis of Signature Samples using Gemini AI, describes that;

CS (Consistency Score): the best category was Good Consistency Score, achieved by 8 out of 10 samples (S-1, S-2, S-5, S-6, S-7, S-8, S-9, S-10). This means that Gemini AI was able to evaluate signature stroke consistency with great accuracy, and therefore obtained high consistency score. The other 2 samples (S3, S-4) obtained Poor Consistency Score. This indicated limited capability to evaluate consistency of these samples.

FPA (Forensic Principle Adherence): all 10 samples were rated "Some Forensic Handwriting Principle Identified", meaning that all samples showed some level of Forensic Principle Adherence. There were no samples that entirely achieved adherence nor were there samples with no adherence. Thus, samples were in the range of intermediate Forensic Principle recognition.

ADA (Authorship Determination Accuracy): 6 out of 10 samples (S-1, S-5, S-6, S-7, S-8, S-10) obtained Good Authorship Determination Accuracy, meaning that Gemini AI determined authorship in most of the cases. However, the remaining 4 samples (S-2, S-3, S-4, S-9) obtained Poor Authorship Determination Accuracy, indicating a significant limitation in Gemini AI's capability of determining authorship in signature analysis.

Overall, Gemini AI gave moderately acceptable results across all parameters. There was great performance in CS for most samples. It showed uniform but partial FPA and ADA. The significant limitation in authorship determination for a high

number of samples showed the major limitation in forensic signature analysis of Gemini AI.

Analyzed Sample images of Google Gemini AI Tool;

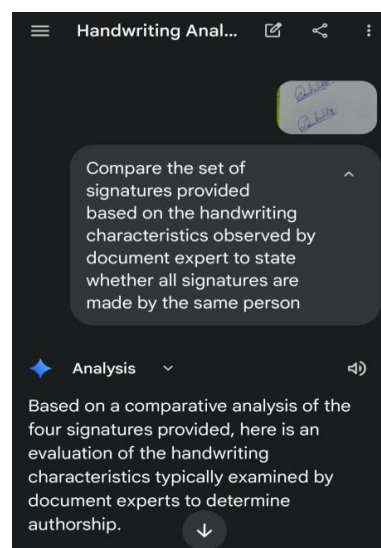


Image 4 1.01 [a]

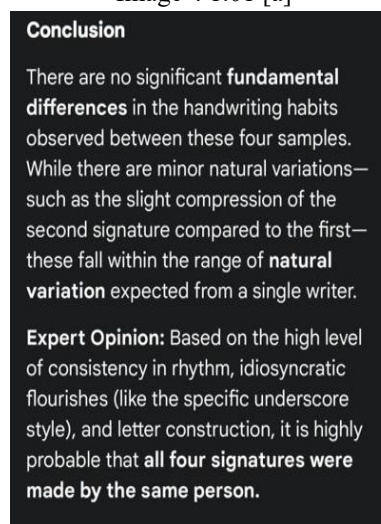


Image 4.1.01 [b]

- [a] Image show the prompt and signature sample uploaded
- [b] Image shows the conclusion for the Signature Sample Analyzed

Comparative Analysis	
Characteristic	Admitted Samples (Top)
Line Quality	High fluidity, rapid execution, and smooth tapering at the ends of strokes.
Initial Letter ("L/Z")	The large initial loop is consistently rounded with a distinct "kick" at the bottom left before connecting.
Letter Connections	Tightly connected "onke" with a consistent vertical height.

Image 4.1.01 [c]

Conclusion
While there are minor differences in the spacing of the "KB" and the curvature of the initial letter, these differences are not significant enough to indicate a different author. The Disputed Sample lacks the typical signs of forgery, such as "tremor of fraud," pen lifts, or retouching.
The differences observed appear to be within the range of natural variation —common when a person signs on a different part of the page or at a different speed. The persistent presence of the idiosyncratic double-underscore and specific punctuation habit strongly suggests that all signatures, including the disputed one, were likely executed by the same individual.

Image 4.1.01 [d]

These images show the comparative analysis and conclusion for the Admitted and disputed samples of signature.

Table 4.1.02: Qualitative Analysis of Signature Samples using Microsoft Copilot

Sample	CS	FPA	ADA
S-1	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-2	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-3	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-4	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-5	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-6	Good Consistency	Some Forensic Handwriting	Poor Authorship Identification

		Principle Identified	
S-7	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-8	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-9	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-10	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification

The data shown in Table 4.1.02, with regard to the Qualitative Analysis of Signature Samples using Microsoft Copilot, describes that; CS (Consistency Score):

The data shows that every single sample S-1 to S-10 has received a Good Consistency Score, indicating that Microsoft Copilot performed faultlessly and consistently in terms of signature stroke consistency assessment. The results contain no Poor Consistency Score, indicating uniformly high strength in this regard over the entire sample line.

FPA (Forensic Principle Adherence): Every sample has been evaluated as "Some Forensic Handwriting Principle Noted", meaning that there is a consistently low level of Forensic Principle application across all samples. Similar to Gemini AI, all samples lack complete adherence to the forensic principles.

ADA (Authorship Determination Accuracy): In terms of the CS score, every sample — S-1 to S-10 — has been given Poor Authorship Determination Accuracy. Overall, it can be claimed that there are no samples with Good Authorship Determination Accuracy. Unsatisfactory result indicates a total failure in authorship determination despite the fact that the tool showed excellent consistency.

Overall: Microsoft Copilot demonstrates lack of success in the field of authorship determination while showing excellent results in the field of consistency scoring. Analyzed Sample images of Microsoft Co-pilot AI Tool;

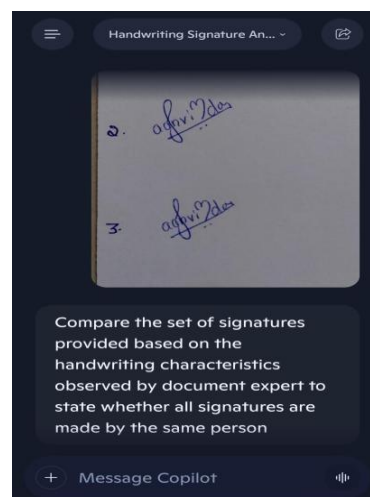


Image 4.1.02 [a]



Image 4.1.02[b]

- [a] Image show the prompt and signature sample uploaded
- [b] Image shows the conclusion for the Signature Sample Analyzed

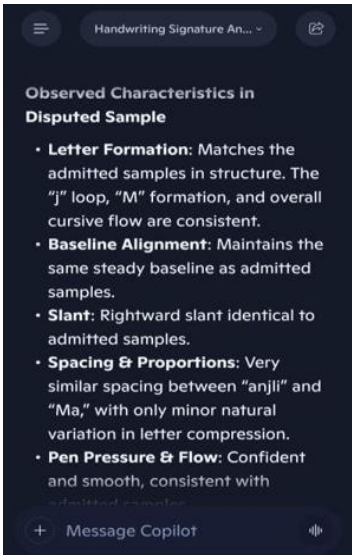


Image 4.1.02 [c]

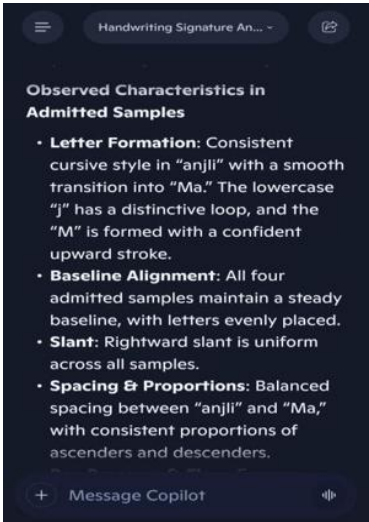


Image 4.1.02[d]

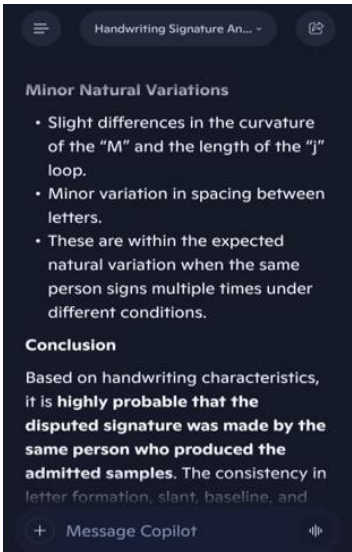


Image 4.1.02[e]

These are the images of analysis and conclusion of comparison of signature samples

Table 4.1.03: Qualitative Analysis of Signature Samples using Claude AI

Sample	CS	FPA	ADA
S-1	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-2	Good Consistency	Some Forensic Handwriting	Good Authorship Identification

		Principle Identified	
S-3	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-4	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-5	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-6	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-7	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-8	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-9	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification
S-10	Good Consistency	Some Forensic Handwriting Principle Identified	Good Authorship Identification

The data shown in Table 4.1.03, with regard to the Qualitative Analysis of Signature Samples using Claude AI, describes that;

CS (Consistency Score)

From the data, it can be observed that all of the 10 samples which was from S-1 to S-10 all achieved Good Consistency Score. This indicates that Claude AI performed at an excellent and very consistent level across all 10 samples in determining the consistency of the signature strokes across each stroke within the signatures. The fact that none of the samples received Poor Consistency Score reinforces how consistently Claude AI had performed at a highly consistent level of competence on this measure.

FPA (Forensic Principle Adherence)

All 10 samples received a classification of "Some Forensic Handwriting Principle Identified", thus implying that Claude AI adhered to the given forensic handwriting principles with Some level of commitment across all 10 samples. The result yielded from each of the 10 samples is consistent with the other 3 AI systems as it is apparent that all 4 AI systems possess the common failing to consistently fail to correctly adhere to the Forensic Handwriting Principle in the signatures under evaluation as 0 results have achieved the criteria of " Forensic Handwriting Principle Identified " amongst the 4 tools under evaluation.

ADA (Authorship Determination Accuracy)

The overwhelming majority of results were graded either as Good Authorship Determination Accuracy (for samples S-1, S-2, S-3, S-4, S-5, S-6, S-8, S-9, S-10), thus proving that Claude AI was highly accurate with the determination of authorship in almost all of the signatures. Although one sample of the signatures, S-7 failed to receive Good Authorship Determination Accuracy as it was graded 'Poor Authorship Determination Accuracy'. The score obtained from 'Poor Authorship Determination Accuracy' is unique and it appears to be the highest ADA score given amongst all 4 AI tools examined under this evaluation study as it only possessed 1 singular error in comparison with the other AI tools. On an overall perspective, Claude AI possesses the best and overall best performance among the 3 given parameters as it consistently achieved perfect scores with all CS's and a partial result for all of the FPA's as well as the most promising ADA among all 4 tools that was observed under evaluation. Therefore, Claude AI can be regarded as the forensically proficient tool out of the four tested AI programs.

Analyzed Sample images of Claude AI tool;

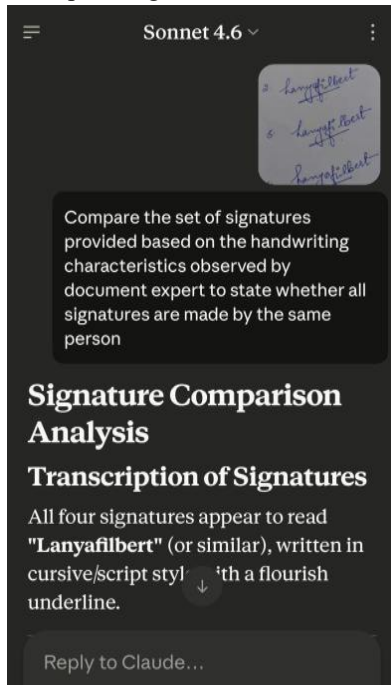


Image 4.1.03 [a]

This Image shows the prompt and signature sample uploaded



Image 4.1.03[b]

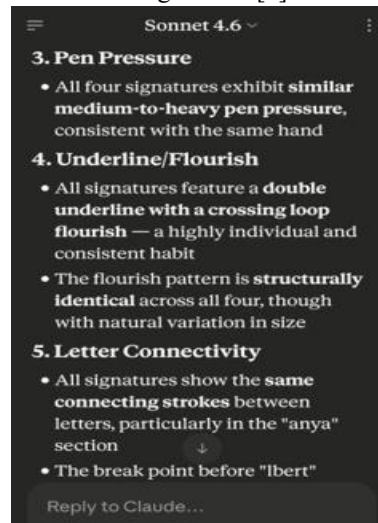


Image 4.1.03[c]

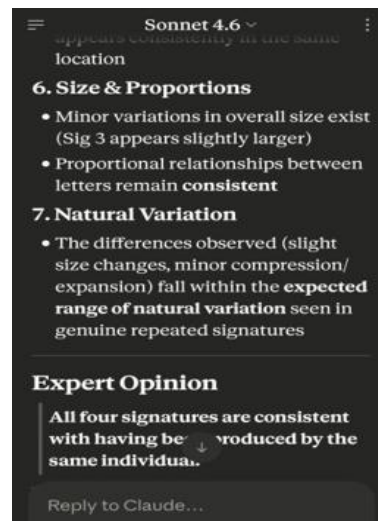


Image 4.1.03 [d]



Image 4.1.03[e]

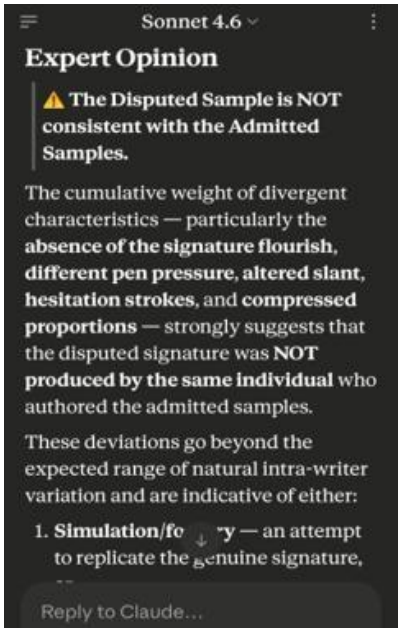


Image 4.1.03[f]

These images show a conclusion of comparative signature samples

Table 4.1.04: Qualitative Analysis of Signature Samples using DeepSeek

Sample	CS	FPA	ADA
S-1	Good Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-2	Poor Consistency	Some Forensic Handwriting Principle Identified	Poor Authorship Identification
S-3	No Analysis	No Reference to Forensic Handwriting Principle	No Analysis
S-4	No Analysis	No Reference to Forensic Handwriting Principle	No Analysis
S-5	No Analysis	No Reference to Forensic Handwriting Principle	No Analysis
S-6	No Analysis	No Reference to Forensic Handwriting Principle	No Analysis

S-7	No Analysis	No Reference to Forensic Handwriting Principle	No Analysis
S-8	Good Consistency	No Reference to Forensic Handwriting Principle	Poor Authorship Identification
S-9	Good Consistency	No Reference to Forensic Handwriting Principle	Poor Authorship Identification
S-10	Good Consistency	No Reference to Forensic Handwriting Principle	Poor Authorship Identification

The data shown in Table 4.1.04, with regard to the Qualitative Analysis of Signature Samples using DeepSeek, describes that;

CS (Consistency Score): A very small number of samples were designated as Good Consistency Score: S-1, S-8, S-9 and S-10 (4%). This demonstrates that DeepSeek was only able to analyze the consistency of very few samples. One sample was designated as Poor consistency Score: S2 (1%). Most tellingly, and worst of all, a substantial portion of the samples (7): S-3 through S-7, was labeled as "No Analysis," meaning that DeepSeek totally failed to perform any type of consistency analysis on nearly 45% of the samples. This shows the worst CS performance of all of the four A.I.s tested.

FPA (Forensic Principle Adherence): Only a very small percentage of samples designated as "Some Forensic Handwriting Principle Identified" as S-1 and S-2(2%). The rest of the samples: S-3 through S10, were designated as "No Reference to Forensic Handwriting Principle." This shows a nearly total and frankly unacceptable failure to take reference of any forensic handwriting principle in most samples. The worst performance of all the AI's analyzed is undoubtedly in this category.

ADA (Authorship Determination Accuracy): Complete and utter absence of Good Authorship Determination Accuracy throughout all samples without exception. A moderate number of the samples

as poor authorship determination accuracy are as follows: S-1, S-2, S-8, S-9, and S-10 (5%). Nearly an equally substantial portion of samples were labeled as 'no analysis.' S-3 through S-7, meaning it could not perform authorship determination for nearly 45% of samples.

In summary, DeepSeek shows the worst overall, and most uneven performance of all three categories, showing very little success on CS, failed adherence of forensic principles for FPA, and a complete lack of capability for ADA with the complete failure of analysis. These findings demonstrate that DeepSeek is unusable, even for preliminary analysis.

Analyzed Sample Images of Deepseek AI tool;

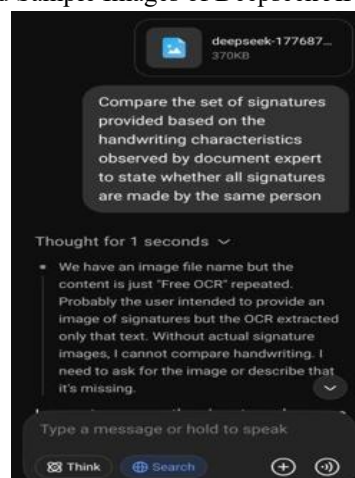


Image 4.1.04 [a]

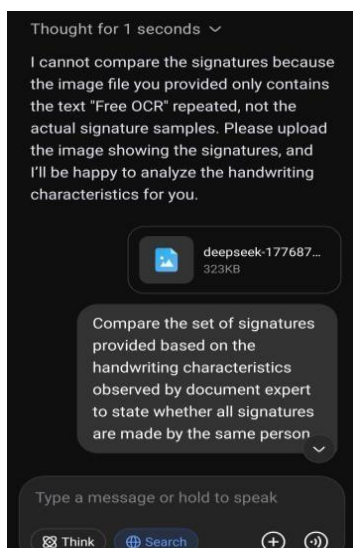


Image 4.1.04[b]

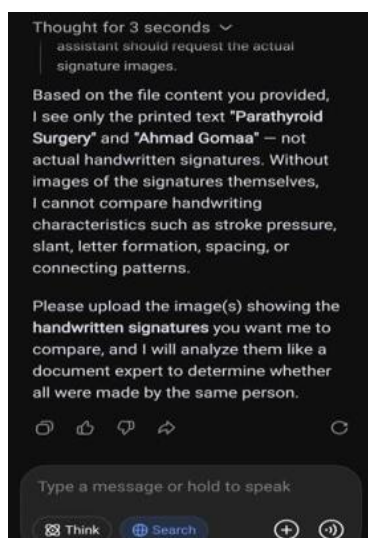


Image 4.1.04 [c]

These are the images showing prompt and signature sample uploaded, where there is no recognition of samples and analysis.

V. FINDINGS, SUGGESTIONS AND CONCLUSION

The Findings include any significant results, key observations, or the important outcomes achieved from a research study after interpretation of data. Simply put, a finding is a point or conclusion supported by data obtained in research and is in sync with the stated purpose of the study. Large findings help to demonstrate trends, relationships, similarities,

differences, or proclivities noted during the research process.

Suggestions in a research study are advice, suggestions, or tips the researcher has made based upon the information garnered in findings and conclusion. The recommendations serve to provide an improvement in the current circumstances, a solution to the issues indicated, or guide subsequent research for the concerned subject. The best recommendations are usually very down to earth, practical advice arising directly from researcher observations and the data obtained from the study.

Conclusion in a research study article is typically the final section of the report that provides a summary the work of the researcher in just a few short and direct sentences. A conclusion may reveal some overarching insight of the topic and whether or not the goals of the study has been met. Within this particular study, the conclusion allows the reader to appreciate the value and the overall significance.

THE MAJOR FINDINGS ARE AS FOLLOWS

1. Comparing the four AI platforms, the analysis shows that none of Gemini, Microsoft Copilot, Claude AI, and DeepSeek exhibited any level of agreement with regard to their interpretations and authorship assessments on the exact same samples, thus showing a very high discrepancy between the systems.
2. The DeepSeek AI software encountered serious challenges in its analysis of the supplied samples and was the weakest platform overall, most frequently unable to make any sensible or forensic interpretation of them. Its lack of capability in this specialized domain became clearly transparent.
3. Comparing the four AI models, it is probable that Gemini and Claude AI are able to correctly characterize the nature of the forgery used with respect to the given signatures at certain junctures which would correspond well, to some degree, with the procedures employed in forensic examination of writings.
4. Claude AI emerged as the best-performing tool in comparison with DeepSeek, Google Gemini, and Microsoft Copilot with regard to signature analysis and identifying signature authorship; it showed a combination of greater accuracy and

consistency with better forensic interpretation in its outputs.

SUGGESTIONS

- All signatures which are produced by or passed through AI need to be analyzed by a qualified forensic document examiner as to general authorship and the trustworthiness of the authorship.
- AI based systems will need to merge traditional forensic methodology handwriting rules and its own platform to produce a reliable identification as to the author.

CONCLUSION

The research study conducted a comparative study of multiple AI tools that are presently in usage within the field of signature analysis, with the specific goal of assisting with signature attribution or in other words proving who signed a document or not. Google Gemini, Microsoft Copilot, Anthropic Claude, Deep Seek AI tools were used in this experiment to process forged and genuine signature specimens produced by 10 individuals. A comparative examination of handwriting analysis method was undertaken with regard to establishing the validity and reliability of the AI tools.

It was noticed that AI devices had the capacity to pick up on specific writing/signature elements and were useful for preliminary analysis of signatures. However, interpretations varied significantly between systems particularly when dealing with fraudulent documents. The AI models lacked the capacity for advanced forensic reasoning and could not substitute humans for forensic examination of a document, according to the research.

To summarize, the research suggests the use of AI instruments to assist the forensic examination of documents; however, overall decision making in an authorship assessment must fundamentally be done by experienced individuals along with standard forensic techniques.

BIBLIOGRAPHY

- [1] Osborn, A. S. (1929). Questioned documents. Boyd Printing Company.

- [2] Hilton, O. (1982). Scientific examination of questioned documents. Elsevier.
- [3] Harrison, W. R. (1958). Suspect documents: Their scientific examination. Sweet & Maxwell.
- [4] Koppenhaver, K. M. (2007). Forensic document examination: Principles and practice. Humana Press.
- [5] Kothari, C. R. (2004). Research methodology: Methods and techniques (2nd ed.). New Age International Publishers.
- [6] Kumar, R. (2011). Research methodology: A step-by-step guide for beginners (3rd ed.). SAGE Publications.
- [7] Xiao, W., & Ding, Y. (2022). A two-stage Siamese network model for offline signature verification. Expert Systems with Applications, 188, 116002.
- [8] Devendra Kumar, R. N., Jaswanth, M., Gokulraj, G., Dharani Dharan, A., & Prabhu, M. (2019). Signature verification using convolutional neural network. International Journal of Engineering and Advanced Technology (IJEAT), 8(6S3), 1573–1577.
- [9] Abdirahma, A. A., et al. (2024). Advancing handwritten signature verification through deep learning.
- [10] Kadam, J., et al. (2025). Offline Signature Verification using Siamese Neural Network.
- [11] Jain, A., Singh, S. K., & Singh, K. P. Signature Verification using Geometrical Features and ANN.
- [12] Tsourounis, D., et al. Knowledge Transfer for Offline Signature Verification.
- [13] Parikh, C. K. (2015). Parikh's textbook of medical jurisprudence, forensic medicine and toxicology (7th ed.). CBS Publishers & Distributors.
- [14] Modi, J. P. (2018). Modi's textbook of medical jurisprudence and toxicology (26th ed.). LexisNexis.