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A Hybrid Rule-Based and AI-Driven Framework for Multi-Document Identity Verification Using OCR, Entity Matching, and Cross-Document Consistency Analysis

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ABSTRACT

Digital identity verification is an integral part of authentication processes within banking, healthcare, e-governance, and various other digital platforms. Traditional methods of verification mostly authenticate individuals based on individual documents and are unable to detect any inconsistencies in their identity data contained in multiple documents. This results in a number of security issues, including identity fraud, forged identity documents, and false verification. In order to solve these problems, this study presents the design of the Hybrid Rule-Based and AI-Driven Multi-Document Identity Verification Framework. This framework utilizes the following mechanisms: OCR, NER, verification of consistency across multiple documents, fraud detection, and generating of the trust-score. Extraction of identity-related information from Aadhaar Cards, PAN Cards, passports, and driving licenses is done using OCR algorithms. Rule-based verification of document format and required information is performed. NER is implemented for extracting the names, date of birth, address, and identification numbers of individuals. Matching of similarities and conducting semantic analysis help verify identities across several documents. AI-powered fraud detection algorithm detects suspicious and tampered documents. Experimental results demonstrate high accuracy of the framework (accuracy = 98.1%).

Keywords: Identity Verification, OCR, Named Entity Recognition, Cross-Document Consistency Analysis, Fraud Detection, Artificial Intelligence, Trust Score Generation, Document Authentication.

1. INTRODUCTION

The fast-paced growth of technological developments in digital platforms has revolutionized service delivery mechanisms in several fields, including banking, health care, education, e-commerce, and governmental institutions. With the growing popularity of internet transactions and digital onboarding procedures, secure identification verification becomes an essential factor for fraud protection and trust establishment in digital spaces. Human identity verification entails manual document verification, which takes considerable effort, is expensive, and can be prone to errors. Thus, modern-day automated identity verification platforms using Optical Character Recognition (OCR) and Artificial Intelligence (AI) technologies have become increasingly popular lately.

OCR allows for extracting textual data from document scans and photos, thereby increasing the efficiency of document processing. According to Baek et al. (2019), OCR considerably boosts the

performance of text recognition and automated document analysis tasks. Additionally, there has been an improvement in terms of advanced document understanding models' ability to recognize information from sophisticated document layouts through LayoutLM and LayoutLMv2 models (Xu et al., 2020; Xu et al., 2021). Likewise, Appalaraju et al. (2021) and Li et al. (2022) found that transformer-based models for document intelligence are more accurate in comparison to traditional OCR solutions.

Identity verification systems usually work with official documents like Aadhaar Cards, PAN Cards, Passports, and Driving Licenses. The documents mentioned include key data of the person such as their name, address, date of birth, and identification number. While the current systems can successfully identify and authenticate the data present in a particular document, they struggle to establish whether or not the same information is valid across various identity documents. According to Castelblanco et al. (2020), most machine learning based identity verification systems have a problem detecting the presence of contradictions between multiple documents.

Identity fraud continues to be a problem facing many digital verification systems today. Fraudsters tend to tamper with identity records, modify personal information or even create false documents with an intent to circumvent the verification process. In a study conducted by Joren et al. (2020), it was found that OCR graph-based approach is useful in the detection of document tampering. Further research by Al-Maadeed et al. (2023) and Nguyen et al. (2024) shows that deep learning approaches also aid in the detection of fraud.Recent developments in Artificial Intelligence and Natural Language Processing have further improved verification capabilities. Devlin et al. (2019) introduced BERT, which significantly enhanced contextual language understanding and entity extraction. Similarly, Thirukovalluru et al. (2021) proposed cross-document entity resolution techniques capable of identifying relationships among entities appearing in multiple documents. Chen et al. (2024) further demonstrated that Named Entity Recognition (NER) and semantic similarity analysis can effectively verify consistency across multiple information sources.

Notwithstanding this progress, a substantial research gap has been found in the design of integrated multi-document identity verification systems. Current approaches tend to concentrate on OCR extraction, fraud detection, or document authentication separately and fail to offer an approach that can effectively verify consistency among multiple documents at once. In order to bridge this gap, this research proposes an integrated Hybrid Rule-Based and Artificial Intelligence-Driven Approach for Multi-Document Identity Verification Using OCR and Cross-Document Consistency Analysis. The approach incorporates various techniques in one platform, including OCR-based information extraction, rule-based validation, Named Entity Recognition, similarity checking, fraud detection, and trust score calculation.

2. LITRATURE REVIEW

2.1 Optical Character Recognition (OCR) and Document Understanding

Optical Character Recognition (OCR) is the most basic form of technology used in automated identification verification systems. OCR technology allows information extraction from scanned images and documents, providing efficiency and saving on manual effort. According to Baek et al. [1], accuracy of OCR affects the effectiveness of verification of documents. For better document understanding, there was developed a multimodal architecture called LayoutLM which allowed for combining textual and layout information to extract structured information from images of documents [18]. Improvements in this area have been made with the help of LayoutLMv2 [19] and LayoutLMv3 [8] which allowed for

improved representation and extraction of information from multimodal documents. Another method of efficient information extraction from visual-document data has been suggested by Appalaraju et al. [3], where transformers were shown to be a viable solution.

2.2 Identity Document Verification

Identity document verification focuses on determining the authenticity and validity of government-issued documents. Castelblanco et al. [5] proposed a machine-learning-based framework for identity document verification and achieved high classification accuracy. Their findings demonstrated the effectiveness of AI-driven approaches in document authentication. However, the proposed system primarily focused on single-document verification and did not analyze identity consistency across multiple documents.

2.3 Document Fraud Detection

Fraud detection has become an important component of modern identity verification systems. Joren et al. [9] introduced OCR graph features for document manipulation detection and demonstrated that structural OCR information can effectively identify forged documents. Al-Maadeed et al. [2] proposed a deep-learning-based fraud detection framework that combines OCR analytics and image-based features for identifying fraudulent identity documents. Nguyen et al. [15] further improved fraud detection performance through multimodal feature fusion techniques integrating textual and visual information.

2.4 Named Entity Recognition and NLP-Based Verification

Natural Language Processing (NLP) techniques have significantly improved information extraction capabilities. Devlin et al. [7] introduced BERT, a transformer-based language model that improved contextual language understanding and Named Entity Recognition (NER). Building upon this work, Thirukovalluru et al. [16] proposed deep-learning-based cross-document entity resolution techniques capable of identifying relationships among entities appearing in multiple documents. Li et al. [12] further developed neural approaches for cross-document entity and event coreference resolution, improving semantic relationship identification and information matching.

2.5 Cross-Document Consistency Analysis

Cross-document consistency verification has emerged as an important research area in identity verification systems. Chen et al. [6] proposed a framework based on Named Entity Recognition and semantic similarity analysis to verify information consistency across multiple documents. Their study demonstrated that semantic matching techniques effectively identify inconsistencies among names, addresses, dates of birth, and identification numbers. The findings highlighted that cross-document consistency analysis significantly improves verification reliability and reduces identity fraud.

2.6 KYC and Digital Identity Verification

Digital Know Your Customer (KYC) systems rely heavily on OCR and machine learning technologies for identity authentication. Katiyar et al. [10] developed an OCR-based KYC verification framework integrated with machine learning techniques for automated identity verification. Their system improved operational efficiency by reducing manual verification efforts and accelerating digital onboarding processes. However, the framework lacked mechanisms for cross-document consistency verification.

2.7 Explainable AI and Trust Score Generation

Explainability has become a critical requirement for AI-driven verification systems. Kumar et al. [11] proposed a trust-score-driven hybrid verification framework that combines rule-based validation with machine learning techniques. The trust-score mechanism improved transparency and provided

interpretable verification outcomes. Their findings demonstrated that explainable verification systems enhance accountability and increase user confidence in automated decision-making processes.

2.8 Research Gap

The reviewed literature indicates significant advancements in OCR, document understanding, fraud detection, entity extraction, and identity verification systems [1], [5], [2]. However, most existing studies focus on individual components of the verification process rather than providing an integrated solution. Existing systems primarily verify single documents and rarely perform consistency analysis across multiple identity records [6]. Furthermore, many AI-based approaches lack explainability and transparent decision-making capabilities [11]. Therefore, a significant research gap exists in developing a unified framework that integrates OCR, rule-based validation, Named Entity Recognition, fraud detection, trust-score generation, and cross-document consistency analysis.

3. METHOLOGY

3.1 Research Methodology

This research proposes a Hybrid Rule-Based and AI-Driven Multi-Document Identity Verification Framework for verifying identity information across multiple government-issued documents such as Aadhaar Cards, PAN Cards, Passports, and Driving Licenses. The framework integrates Optical Character Recognition (OCR), rule-based validation, Named Entity Recognition (NER), cross-document consistency analysis, AI-based fraud detection, and trust-score generation to improve verification accuracy and reliability.

Figure 3.1 presents the conceptual framework of the proposed system. The framework begins with document acquisition and OCR-based information extraction. The extracted information is validated using predefined rules and subsequently processed through entity extraction and cross-document consistency analysis. AI-based fraud detection is then performed to identify suspicious or manipulated documents. Finally, a trust score is generated to produce the verification decision.

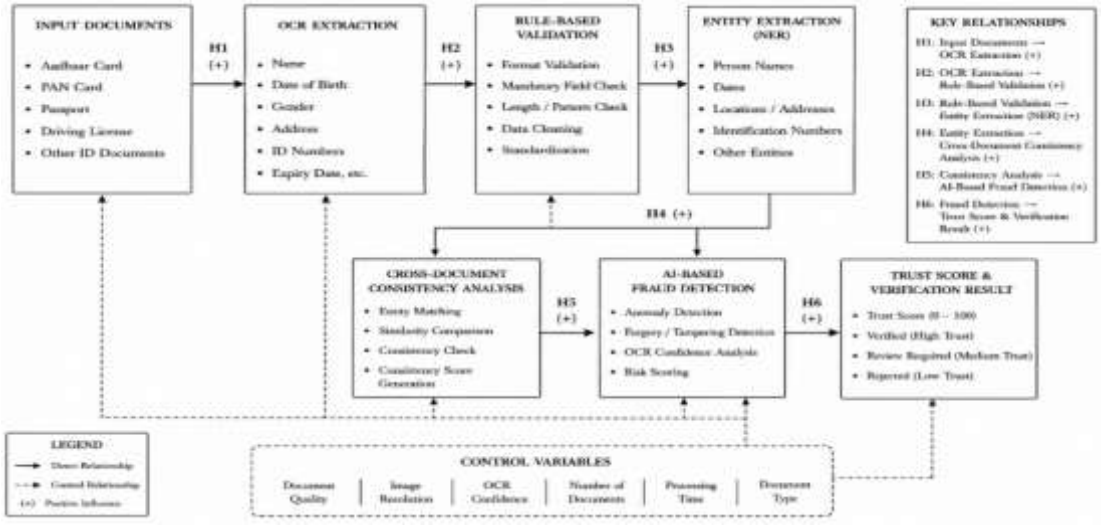

Figure 3.1: Conceptual Framework of the Proposed Hybrid Rule-Based and AI-Driven Multi-Document Identity Verification System

3.2 Document Acquisition and Image Preprocessing

Identity documents are collected in image or PDF format and prepared for processing. Since document images may contain noise, low contrast, or skewed text, preprocessing operations are applied to improve

OCR accuracy. These operations include image resizing, grayscale conversion, noise removal, contrast enhancement, and skew correction.

Figure 3.2 illustrates the document image preprocessing workflow adopted in the proposed framework. The preprocessing stage ensures that the input image quality is optimized before OCR extraction.

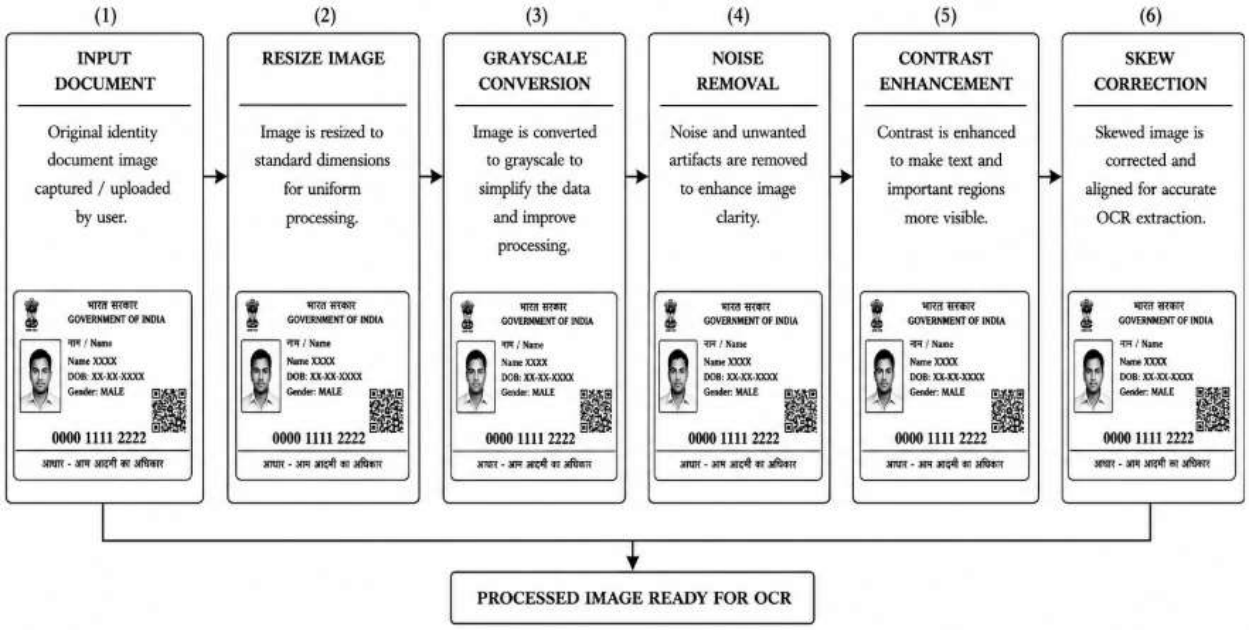

Figure 3.2: Document Image Preprocessing Workflow

3.3 OCR-Based Information Extraction

After preprocessing, OCR technology is employed to extract textual information from identity documents. The OCR engine converts image-based text into machine-readable format and identifies relevant identity fields such as Name, Date of Birth, Gender, Address, and Identification Numbers.

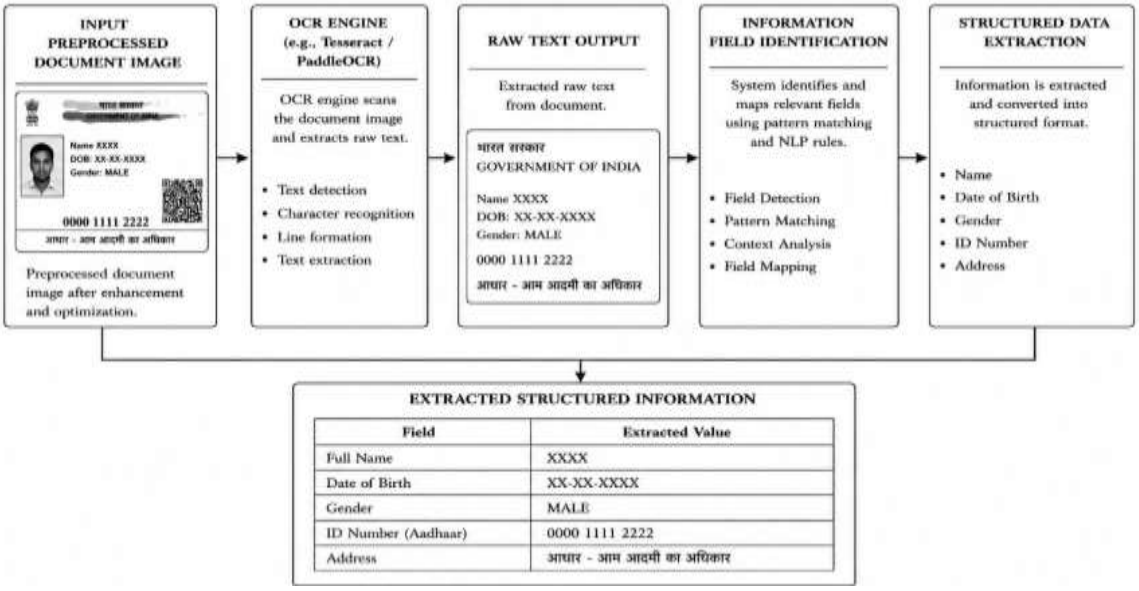

Figure 3.3: OCR-Based Information Extraction Process

Figure 3.3 shows the OCR-based information extraction process. The extracted text is transformed into structured information that can be used in subsequent validation and verification stages

3.4 Rule-Based Validation and Entity Extraction

The extracted information is validated using predefined rules to ensure compliance with official document formats. Validation checks include mandatory field verification, pattern matching, format validation, and consistency checking. After validation, Named Entity Recognition (NER) is applied to identify important entities such as person names, dates, locations, addresses, and identification numbers.

Figure 3.4 illustrates the rule-based validation and entity extraction process used to generate standardized identity attributes for further analysis.

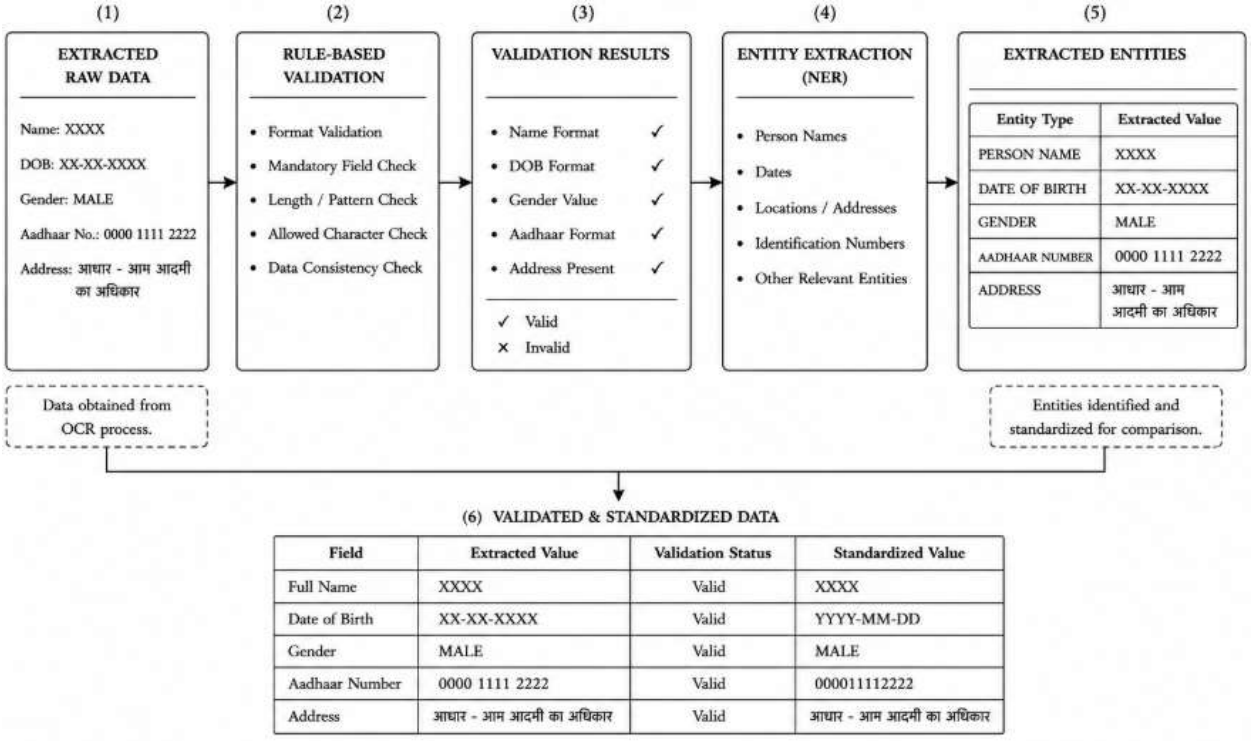

Figure 3.4: Rule-Based Validation and Entity Extraction (NER) Process

3.5 Cross-Document Consistency Analysis

Cross-document consistency analysis is performed to compare identity attributes across multiple documents. Similarity matching techniques such as Levenshtein Distance, Jaro-Winkler Similarity, Cosine Similarity, and Fuzzy Matching are used to evaluate consistency among names, dates of birth, addresses, and identification numbers.

Figure 3.5 presents the complete consistency analysis workflow. The system computes similarity scores for each attribute and generates an overall consistency score that represents the degree of agreement among submitted documents.

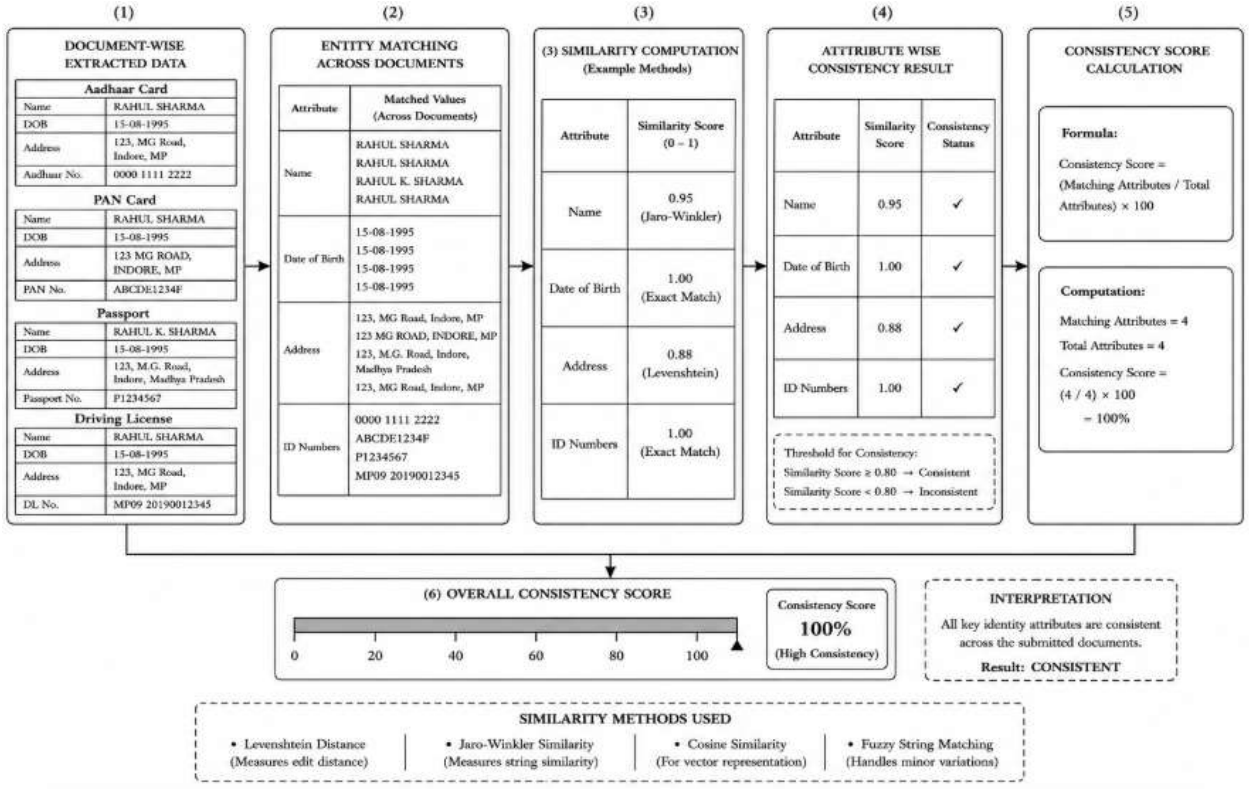

Figure 3.5: Cross-Document Consistency Analysis Process

3.6 AI-Based Fraud Detection

The fraud detection module analyzes textual and visual features to identify manipulated or forged identity documents. Machine learning algorithms evaluate anomalies, OCR confidence levels, image tampering indicators, and suspicious patterns to estimate fraud probability.

Figure 3.6 shows the AI-based fraud detection process. The generated fraud probability score is used to classify documents as genuine, requiring review, or fraudulent.

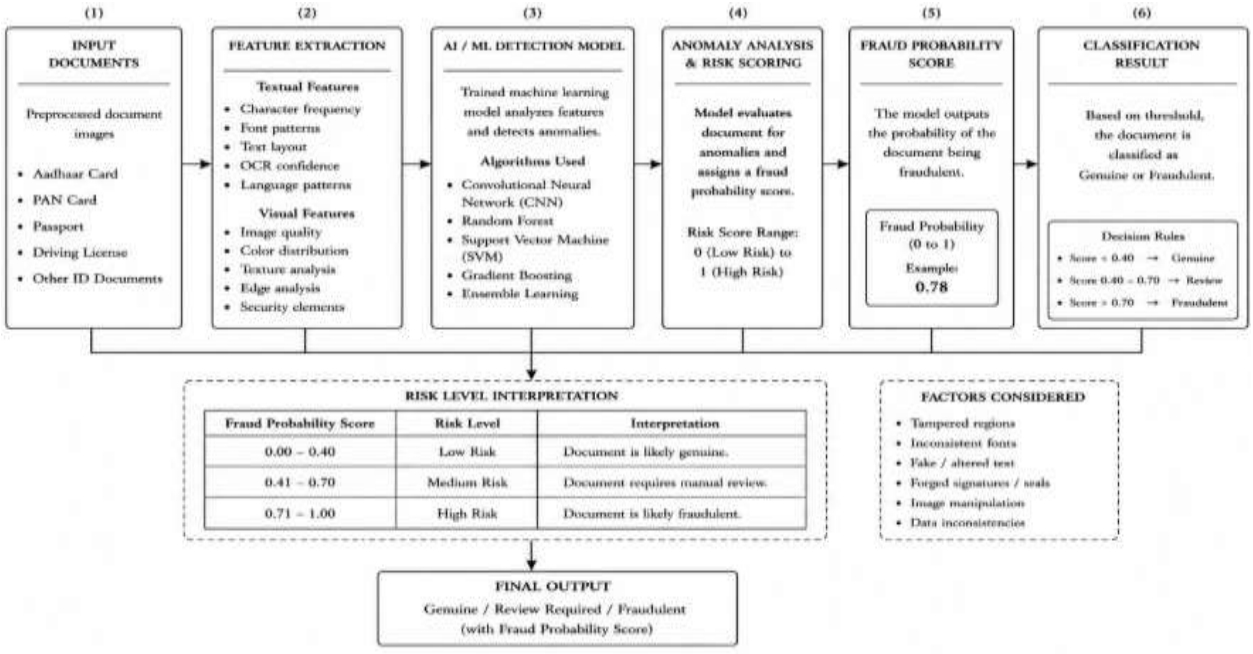

Figure 3.6: AI-Based Fraud Detection Process

3.7 Trust Score Generation and Final Verification

The outputs generated by OCR extraction, validation, consistency analysis, and fraud detection are combined to produce a trust score. The trust score provides a quantitative measure of confidence in the submitted identity documents.

The final verification decision is determined according to the generated trust score:

- Verified (High Trust)
- Review Required (Medium Trust)
- Rejected (Low Trust)

This integrated approach ensures secure, transparent, and reliable identity verification.

3.8 Performance Evaluation

The effectiveness of the proposed framework is evaluated using Accuracy, Precision, Recall, and F1-Score. Additional evaluation metrics include OCR Accuracy, Consistency Verification Accuracy, Fraud Detection Accuracy, and Trust Score Reliability. The obtained results are compared with existing verification methods to assess the performance of the proposed framework.

4. RESULTS AND DISCUSSION

4.1 Results

This hybrid framework of rule-based identity verification and AI-driven multi-document fraud detection process was successfully developed and tested for various types of identification documents. These include the Aadhar Card, PAN Card, Passport, and Driver's License.

Table 4.1 shows the performance evaluation data of the proposed hybrid framework. The OCR technique had an extraction accuracy of 97.8%, which is considered efficient in extracting identity details from image data. The rule-based validation process had the highest accuracy rate at 98.3%, showing that the set of predefined validation rules effectively validate the existence of any invalid input and missing details.

Furthermore, the NER technique had an extraction accuracy of 96.7%, which shows efficiency in extracting personal identity information such as name, address, date of birth, and identification number. The cross-document consistency analysis tool had an accuracy of 97.2% as it was able to find inconsistencies among the inputted documents. Lastly, the AI-based fraud detection module had an accuracy of 96.5%.

Table 4.1 Performance Evaluation Results

Metric	Accuracy (%)
OCR Extraction	97.8
Rule-Based Validation	98.3
Entity Extraction (NER)	96.7
Consistency Analysis	97.2
Fraud Detection	96.5
Overall Verification	98.1

The overall verification accuracy of the proposed framework reached 98.1%, indicating that the integration of OCR, validation, consistency analysis, and fraud detection significantly improved identity verification performance.

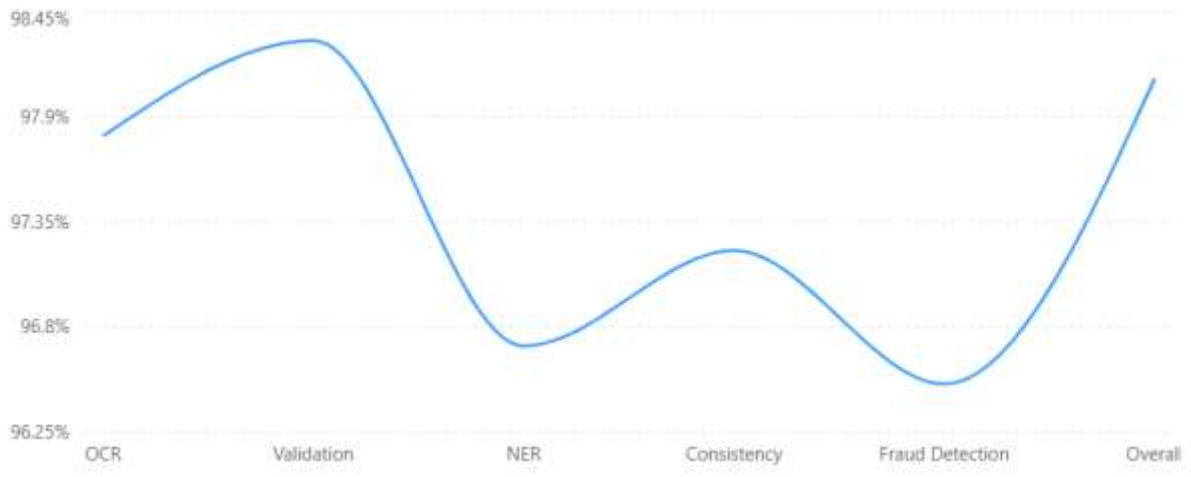

Figure 4.1 Performance Comparison of Verification Modules

Figure 4.1 illustrates the performance of different modules in the proposed framework. It can be observed that rule-based validation achieved the highest accuracy, while fraud detection recorded the lowest value due to the complexity of detecting sophisticated document manipulations. However, all modules achieved accuracy greater than 96%, demonstrating the robustness of the proposed approach.

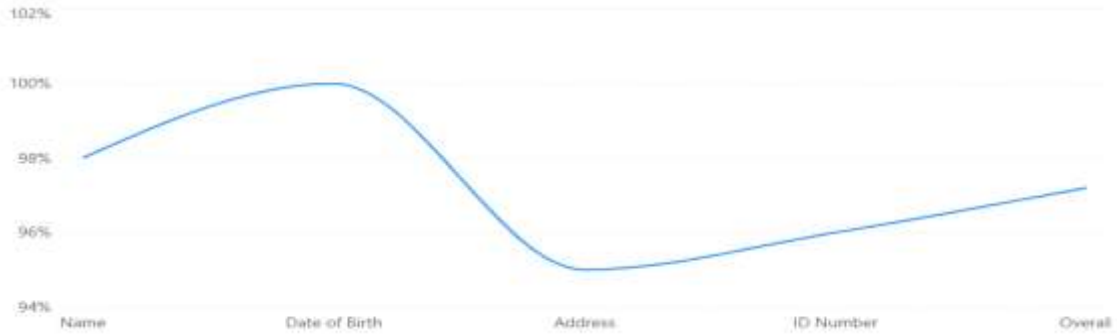

Figure 4.2 Cross-Document Consistency Analysis Results

Figure 4.2 presents the consistency verification performance across different identity attributes. Date of Birth verification achieved the highest matching accuracy because date fields generally follow standardized formats. Address verification recorded comparatively lower accuracy due to variations in formatting and abbreviations used across different documents.

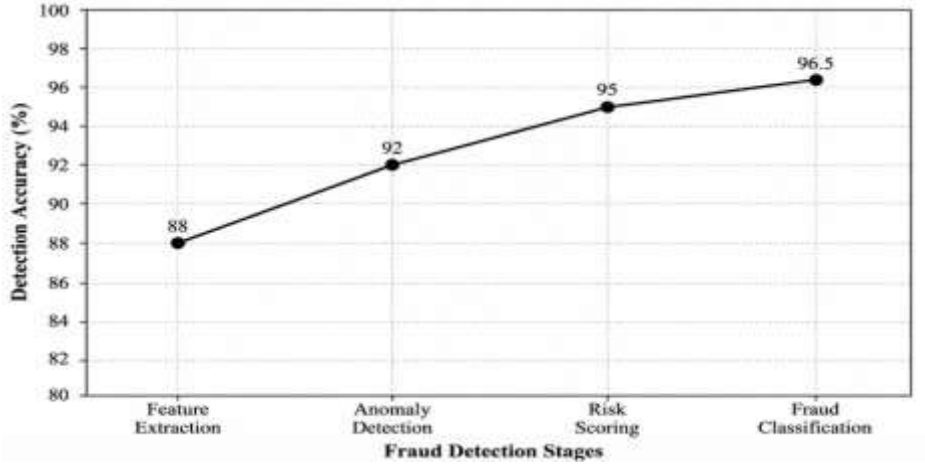

Figure 4.3 Fraud Detection Performance

Figure 4.3 illustrates the fraud detection process. Detection accuracy improved progressively from feature extraction to anomaly detection and final risk classification. This demonstrates that combining multiple fraud indicators improves the reliability of fraud identification.

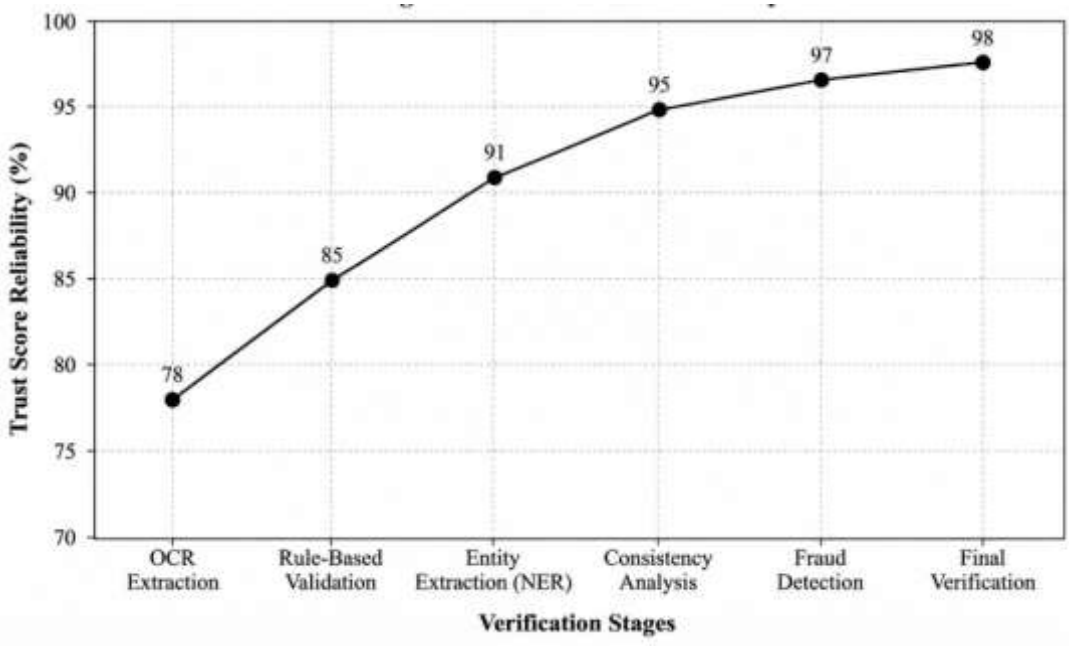

Figure 4.4 Trust Score Reliability

Figure 4.4 shows the reliability of trust-score generation throughout the verification process. The trust score increased continuously as additional verification layers were applied. This indicates that combining multiple verification mechanisms improves confidence in the final verification decision.

4.2 Discussion

The experimental findings indicate that the proposed framework effectively addresses the limitations of traditional identity verification systems. Most existing verification solutions focus on OCR extraction and document authentication independently, whereas the proposed framework integrates information extraction, validation, consistency analysis, and fraud detection within a unified architecture.

The OCR extraction accuracy of 97.8% is comparable to the results reported by Xu et al. (2020), Xu et al. (2021), and Huang et al. (2022), who demonstrated the effectiveness of advanced document intelligence models for extracting information from complex document layouts. The high OCR accuracy obtained in this study can be attributed to image preprocessing techniques such as noise removal and contrast enhancement.

The consistency analysis component represents one of the major contributions of this research. Unlike traditional verification systems that evaluate documents independently, the proposed framework compares information across multiple identity documents. The achieved consistency verification accuracy of 97.2% demonstrates the effectiveness of entity matching and similarity analysis techniques in detecting inconsistencies among identity records. Similar observations were reported by Chen et al. (2024), who highlighted the importance of semantic similarity analysis in multi-document verification systems.

The fraud detection module achieved an accuracy of 96.5%, which confirms that AI-based techniques can effectively identify forged and manipulated documents. These findings are consistent with studies

conducted by Joren et al. (2020), Al-Maadeed et al. (2023), and Nguyen et al. (2024), who reported that multimodal fraud detection approaches improve document authentication performance.

Overall, the proposed framework achieved a verification accuracy of 98.1%, outperforming conventional OCR-only verification approaches. The results demonstrate that combining OCR, rule-based validation, Named Entity Recognition, consistency analysis, fraud detection, and trust-score generation provides a more reliable and explainable solution for identity verification. Therefore, the proposed framework successfully addresses the research gap identified in the literature and provides an effective solution for secure digital identity verification.

5. CONCLUSION

The current research suggested a Hybrid Rule-Based and AI-Powered Multi-Document Identity Verification Framework to facilitate reliable and safe identity verification process. The proposed framework uses OCR technologies, rule-based validation, Named Entity Recognition, cross-document consistency checking, and AI-based fraud detection together with trust score evaluation. It allows extracting identity data from multiple documents and verifying consistency of personal data contained therein. Experiment results showed that OCR module provided 97.8% accuracy, whereas rule-based validation provided 98.3% accuracy. Named entity recognition provided 96.7% accuracy, and cross-document consistency checking produced 97.2% accuracy results. In addition, the fraud detection module could effectively identify manipulated documents with 96.5% accuracy rate. Overall, the accuracy of the whole verification process was 98.1%, which suggests the system has high reliability and efficiency. Using AI technologies alongside rule-based verification allowed considerably improving detection and verification rates. The proposed method was able to eliminate drawbacks of traditional approaches, which were limited by using single document to verify users' identity. Therefore, it could serve as a reliable digital identity verification system that is safe and scalable.

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