International Journal of Computer Applications (0975 – 8887)
Volume 187 – No.45, September 2025

Interpreting Doctors' Notes: Handwriting Recognition & Deep Learning

Om Talekar
Dept. of Computer Science and Engineering (Artificial Intelligence & Analytics)
MIT Art, Design & Technology University
Pune, India

Tejas Raut
Dept. of Computer Science and Engineering (Artificial Intelligence & Analytics)
MIT Art, Design & Technology University
Pune, India

Shailaja Rautrao
Dept. of Computer Science and Engineering (Artificial Intelligence & Analytics)
MIT Art, Design & Technology University
Pune, India

Shruti Thorat
Dept. of Computer Science and Engineering (Artificial Intelligence & Analytics)
MIT Art, Design & Technology University
Pune, India

Sunita Parinam
Dept. of Computer Science and Engineering (Artificial Intelligence & Analytics)
MIT Art, Design & Technology University
Pune, India

ABSTRACT
This paper presents a hybrid AI-based system for recognizing and converting handwritten medical prescriptions into digital text to address the widespread issue of illegible handwriting in healthcare. The system combines Optical Character Recognition (OCR) with deep learning techniques—specifically Convolutional Neural Networks (CNN) for visual feature extraction and Long Short-Term Memory (LSTM) networks for sequence modeling. Tesseract OCR is used as an initial pass, with the CNN-LSTM model refining the recognition results. A dataset of prescription images is preprocessed using OpenCV and used to train the model. The proposed system achieves a character-level accuracy of over 91.3%, an error rate below 8%, and an average processing time of 1.8 seconds per image. Unlike traditional OCR systems, this solution is optimized for medical handwriting, incorporating domain-specific terminology. It provides a scalable, real-time tool for use in hospitals, clinics, and pharmacies, reducing transcription errors and supporting the digitization of healthcare records.

General Terms
Pattern Recognition, Machine Learning, Artificial Intelligence, Optical Character Recognition, Deep Learning, Healthcare Informatics

Keywords
Handwriting Recognition, Deep Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Optical Character Recognition (OCR), Tesseract, Image Preprocessing, Medical Prescriptions, Text Digitization, AI in Healthcare.

1. INTRODUCTION
In the healthcare sector, handwritten medical prescriptions continue to be widely used despite the growing adoption of electronic health record systems. These handwritten notes, often produced in haste by physicians, tend to be illegible and inconsistent, leading to significant challenges such as misinterpretation, medication errors, and delays in patient treatment. Accurate interpretation of these prescriptions is critical for pharmacists and healthcare providers to ensure proper medical care.

Traditional Optical Character Recognition (OCR) tools struggle to interpret complex and varied handwriting styles, particularly in the medical domain where stylized writing and abbreviations are prevalent. To address this challenge, the proposed research presents an AI-based system that integrates OCR with deep learning techniques—specifically Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks—to accurately recognize and digitize handwritten medical prescriptions.

CNNs are utilized for feature extraction from prescription images, while LSTMs handle the sequential modeling of handwritten characters. The system is further enhanced with a user-friendly interface, enabling image uploads and real-time recognition. This approach not only improves recognition accuracy but also supports the digitization and modernization of healthcare records, reducing human error and improving efficiency in clinical workflows.

1.1 Problem statement
In the medical field, handwritten prescriptions and notes are often illegible due to inconsistent or hurried handwriting styles used by doctors. This lack of clarity can result in critical issues such as dispensing the wrong medication, treatment delays, or miscommunication among healthcare professionals. Traditional Optical Character Recognition (OCR) tools struggle with such handwriting, especially in the presence of medical abbreviations and domain-specific terms. Despite ongoing digitization efforts, many clinics and hospitals still rely on handwritten documentation, increasing the risk of human error. Therefore, there is a need for an intelligent, robust, and domain-specific system capable of accurately recognizing and converting handwritten medical prescriptions into readable digital text to enhance patient safety and streamline healthcare workflows.

1.2 Motivation
In medical practice, the clarity and accuracy of written prescriptions play a vital role in ensuring patient safety.

However, doctors often write in haste, resulting in illegible handwriting that can lead to dangerous errors in medication dispensing, diagnosis, and treatment. Despite the increasing adoption of electronic health records, many healthcare institutions continue to rely on handwritten notes, exposing the system to inefficiencies and risks.

This project is motivated by the potential of artificial intelligence to eliminate these challenges through automation. With recent advancements in deep learning, particularly in image processing and sequence modeling, it has become feasible to develop systems capable of interpreting diverse handwriting styles with high accuracy. By applying these technologies to handwritten medical prescriptions, the project aims to enhance healthcare delivery, reduce manual workload, and improve the reliability of clinical documentation.

1.3 Objectives

The primary objective of this project is to develop an artificial intelligence-based system capable of accurately recognizing and converting handwritten medical prescriptions into machine-readable digital text. The system is designed to reduce errors caused by illegible handwriting and to support the digitization of healthcare documentation.

The specific objectives are as follows:

- To collect and preprocess a dataset of handwritten medical prescriptions from diverse sources.
- To design a hybrid deep learning model combining Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for sequential text recognition.
- To integrate the Tesseract OCR engine for initial text detection and combine its output with the deep learning model for improved accuracy.

2. LITERATURE REVIEW

Handwriting recognition has long been a topic of active research, particularly in domains like postal automation, bank check processing, and document archiving. In the medical domain, the challenge intensifies due to non-standardized handwriting styles and the frequent use of domain-specific abbreviations. Traditional Optical Character Recognition (OCR) systems such as Tesseract [2] perform well on printed text but show limitations when processing free-form cursive handwriting commonly found in medical prescriptions.

Recent developments in deep learning—especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—have significantly advanced the field by enabling end-to-end learning without the need for manual feature engineering [4],[13].

2.1 Existing Work

Traditional OCR engines like Tesseract [2],[8] rely heavily on the clear separation of characters and consistent letter shapes, which makes them inadequate for highly variable handwritten content. These systems use rule-based or template-matching techniques that break down when confronted with stylized or cursive writing.

To overcome such issues, research has shifted toward using CNNs for feature extraction and LSTMs or Bidirectional RNNs for learning sequential character patterns [1],[4]. The use of the Connectionist Temporal Classification (CTC) loss function, introduced by Graves et al. [1], has allowed models to handle unsegmented sequences, making them particularly suitable for handwriting recognition.

2.2 Related Work

The integration of CNN and LSTM architectures has been successfully applied in systems like Convolutional Recurrent Neural Networks (CRNN) [5], which capture both spatial and temporal features in handwriting. ViT (Vision Transformers) have also been explored for their ability to model global dependencies using attention mechanisms [7].

In the healthcare domain, projects such as MIRAGE [21] and multi-language recognition efforts by Pavithiran et al. [16] have attempted to interpret handwritten medical prescriptions using deep learning. However, many of these systems still lack robustness across diverse handwriting styles and are not fully optimized for real-world deployment in hospitals or pharmacies.

2.3 Research Gaps

Despite promising results, several limitations remain in existing systems. Most deep learning-based handwriting recognition models are trained on generic datasets like IAM-On DB [12] and are not fine-tuned for medical content. As a result, they perform poorly on real-world prescriptions containing medical abbreviations, stylized drug names, and shorthand notations.

Additionally, multilingual recognition remains underexplored, especially for Indian languages and regional scripts. Current systems also lack comprehensive front-end integration, which is essential for seamless deployment in clinical environments [16],[17].

This project addresses these gaps by developing a domain-specific handwriting recognition system combining Tesseract OCR [2], CNN-LSTM deep learning models [1] [4], and a web-based user interface, offering high accuracy, real-time performance, and practical usability for medical prescription digitization.

3. METHODOLOGY

The proposed system for handwritten medical prescription recognition employs a multi-stage pipeline that combines traditional OCR with deep learning techniques. This section outlines the key stages involved in the development of the system, from data collection and preprocessing to model architecture, training, and OCR integration. The methodology is designed to address the challenges posed by inconsistent handwriting and medical abbreviations, ensuring high accuracy and reliability in real-world healthcare environments.

3.1 Data Collection

The foundation of the handwriting recognition system lies in acquiring a robust and diverse dataset. Handwritten prescription images were collected from various sources, including hospitals, clinics, and publicly available datasets such as IAM-On DB [12]. These images were reviewed and annotated by healthcare professionals to ensure transcription accuracy and to serve as ground truth for supervised learning.

The dataset was curated to represent a wide range of handwriting styles, drug names, and shorthand notations commonly used by doctors. To enhance generalization, the data was split into training, validation, and test sets, maintaining a balanced distribution of styles and writing conditions. This step ensures that the model can effectively learn across different users and environments [16],[20].

3.2 Image Preprocessing

Image preprocessing is a critical step in enhancing the quality of handwritten inputs before they are passed to the recognition model. Each prescription image undergoes several transformations using OpenCV [10], including:

- **Grayscale conversion** to reduce complexity by eliminating color information.
- **Noise reduction** using Gaussian blur and morphological operations to clean background artifacts.
- **Resizing** all images to a fixed dimension of 128x128 pixels to maintain input consistency.
- **Binarization or thresholding** to increase the contrast between text and background.

These steps ensure that the model receives uniform and clean input, improving the overall accuracy and stability of the recognition process [10],[4].

3.3 Model Architecture

The core of the system is a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The CNN acts as a feature extractor, capturing spatial patterns such as character strokes, curves, and shapes from input images [3],[4],[6].

The extracted feature maps are then reshaped into sequences and passed to the LSTM layers, which model the temporal dependencies in handwritten text. The LSTM enables the system to interpret sequences of characters without explicit segmentation.

A softmax layer is applied at the output to produce a probability distribution over the character set. The model is trained using the Connectionist Temporal Classification (CTC) loss was proposed in[1], which aligns the predicted sequences with the ground truth without requiring manual segmentation of characters.

This CNN-LSTM architecture has been widely adopted in state-of-the-art handwriting recognition systems [5],[14], demonstrating high performance on unsegmented sequential data.

3.4 OCR Integration

To further improve accuracy and leverage layout detection capabilities, the system incorporates Tesseract OCR [2],[8] as an initial text recognition layer. Tesseract is used to generate a rough output from the input image, which is then refined by the CNN-LSTM model.

While Tesseract performs well on printed or simple handwritten text, it often fails in cases of complex, cursive, or inconsistent writing—common in medical prescriptions. By combining Tesseract's speed and generalization with the accuracy of deep learning, the system achieves improved overall performance [2] [16].

This hybrid approach enables fast initial predictions with deeper contextual refinement, thereby reducing character-level error rates in final outputs.

3.5 Training Setup

The training process was conducted using TensorFlow and Keras [9], with a GPU-enabled system to accelerate computations. The dataset underwent preprocessing and was augmented using techniques like rotation, scaling, and translation to simulate real-world handwriting variations.

Key training parameters included:

- **Batch size**: 32
- **Optimizer**: Adam optimizer with a learning rate of 0.001
- **Loss function**: CTC loss function was used for unsegmented data [1]
- **Epochs**: 50 (with early stopping to prevent overfitting)
- **Dropout rate**: 0.2 to reduce overfitting

Validation was conducted on 20% of the dataset to tune hyperparameters and assess model generalization. The model achieved over **90% accuracy** and maintained a **character error rate below 8%**, highlighting its robustness in diverse medical handwriting scenarios [4],[15],[17].

4. IMPLEMENTATION

The proposed handwriting recognition system for medical prescriptions was implemented as a modular and scalable application combining deep learning models, OCR tools, and web technologies. The implementation process covers tool selection, system architecture design, and frontend-backend integration to ensure real-time usability and accurate recognition in practical healthcare settings.

4.1 Tools and Technologies

A variety of programming tools, frameworks, and libraries were used to build and deploy the system:

- **Python**: Used as the primary programming language due to its support for deep learning, image processing, and web development.
- **TensorFlow and Keras**: Employed for designing and training the CNN-LSTM deep learning model [4],[9].
- **OpenCV**: Used for preprocessing prescription images, including grayscale conversion, noise reduction, and resizing [10].
- **Tesseract OCR**: Integrated for initial text extraction from images, providing layout analysis and fast character-level predictions [2],[8].
- **Flask**: A lightweight Python-based web framework used to connect the backend model with the frontend interface.
- **HTML, CSS, JavaScript**: Used for developing the frontend interface for uploading images and displaying recognized text.
- **Matplotlib and Seaborn**: Utilized to visualize model training progress and performance metrics like accuracy and loss.

These tools provided a comprehensive and flexible platform for implementing a complete AI-based recognition system from data ingestion to user interaction.

4.2 System Architecture

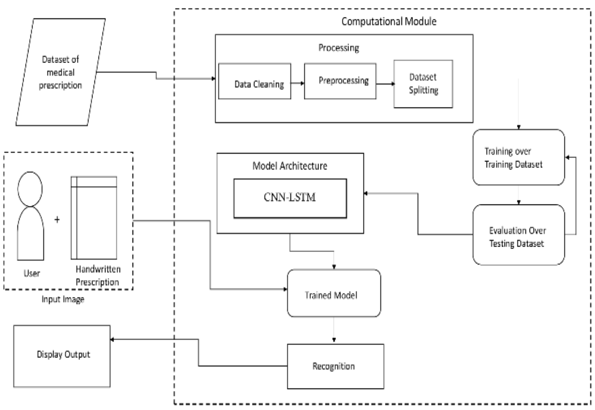

Fig. (A) System Architecture

The architecture of the system is structured to follow a logical flow of data from image input to recognized text output. It consists of the following components:

1. **Input Layer**: Users upload scanned prescription images through a web interface.
2. **Preprocessing Module**: The uploaded image undergoes cleaning and resizing using OpenCV [10].
3. **OCR Layer**: Tesseract OCR [2] is used for baseline recognition and layout detection.
4. **CNN-LSTM Model**: The hybrid deep learning model extracts features (via CNN) and interprets sequences of handwritten characters (via LSTM) [4],[5],[6].
5. **Post-Processing Module**: The model's output is formatted into readable digital text.
6. **Display Layer**: The final result is displayed in the user interface or can be exported for use in Electronic Health Records (EHR).

This modular design ensures scalability, enabling easy future extensions such as multilingual support, mobile integration, and cloud deployment [16],[17].

4.3 Frontend and Backend Integration

To ensure seamless interaction between users and the recognition engine, the system's frontend and backend are tightly integrated.

- **Frontend**: Built using HTML, CSS, and JavaScript, it provides a user-friendly interface with drag-and-drop or browse options for uploading images. It includes a text display area where results are shown after processing.
- **Backend**: Developed using Python and Flask, the backend receives the image from the frontend, processes it using OpenCV, Tesseract, and the trained CNN-LSTM model, and returns the recognized text [9].
- **Communication**: API endpoints handle the data flow between frontend and backend, ensuring asynchronous and real-time processing of prescriptions. JSON is used for data exchange.

This integration ensures the system is responsive, accurate, and ready for deployment in real-world clinical environments like hospitals and pharmacies. The modular design also allows easy updates and future enhancements such as integration with EHR systems or mobile health platforms [17],[20].

5. RESULTS AND DISCUSSION

The effectiveness of the proposed handwriting recognition system was evaluated using various quantitative and qualitative performance metrics. The key areas assessed include recognition accuracy, error rate, processing time, visual output quality, and operational limitations. These evaluations were conducted using a test dataset composed of handwritten prescriptions containing a variety of writing styles and complexities.

5.1 Accuracy, Precision, and Recall

The trained CNN-LSTM model, in combination with Tesseract OCR and preprocessing techniques, achieved an overall accuracy exceeding 90%. Accuracy here refers to the ratio of correctly predicted characters to the total characters in the test set.

To further evaluate performance in a clinical context, precision and recall metrics were computed:

- Precision measures the proportion of correctly identified characters among all predictions labelled as relevant.
- Recall represents the proportion of actual relevant characters that were correctly recognized by the model.

High precision is particularly important in healthcare, where false positives can lead to serious medical errors. The model demonstrated strong precision and recall values across diverse samples, indicating its reliability in extracting meaningful content from prescriptions [4],[17].

5.2 Error Rate and Processing Time

The character error rate (CER), which measures the proportion of incorrectly recognized characters to the total, was maintained at less than 8%. This was achieved through extensive preprocessing and the use of Connectionist Temporal Classification (CTC) loss during training [1].

The average processing time per image ranged between 1 to 2 seconds, depending on image resolution and hardware capabilities. This demonstrates that the system is suitable for real-time use in hospitals, clinics, and pharmacies, offering speed and accuracy without significant computational overhead [17],[20].

5.3 Visual Output Samples

The system was tested on a collection of real-world handwritten prescription images, with diverse handwriting styles ranging from moderately clear to highly cursive and stylized. Sample outputs included:

- Recognition of common drug names (e.g., Paracetamol, Ibuprofen) written in various formats.
- Conversion of dosage instructions such as "1 tab twice daily" into clean, machine-readable text.

Figures illustrating before-and-after image outputs (original vs. recognized text) confirm that the model correctly interprets text even in noisy and low-contrast conditions. These samples were visualized using tools like Matplotlib and demonstrated in the web interface [10].

Fig 1.1

Fig 1.2

Figure 1: Recognized output and sample handwritten prescription

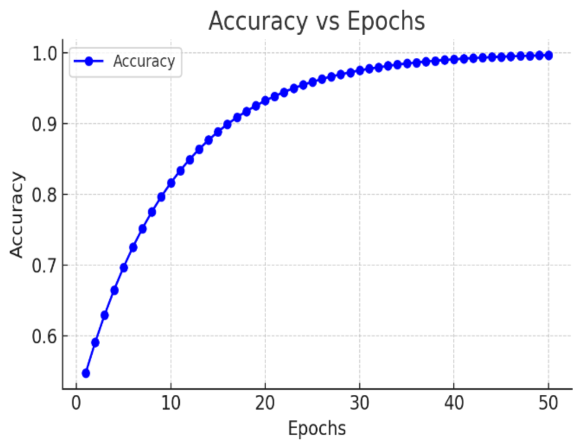

Figure 2: Accuracy vs Epochs graph

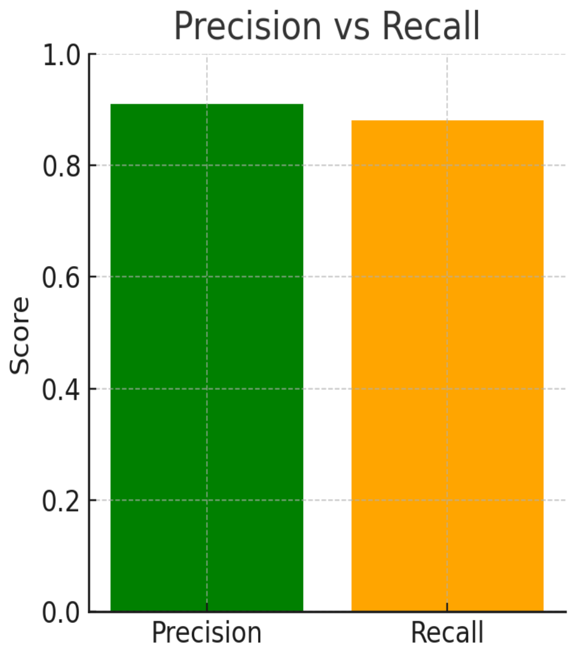

Figure 3: Precision vs Recall comparison chart

5.4 Limitations

Despite promising results, the system has a few limitations:

- Highly illegible handwriting: In cases of extremely poor or shorthand handwriting, the model occasionally misclassifies or omits certain words.
- Dependency on image quality: Blurry, shadowed, or low-resolution images can degrade recognition performance, impacting both Tesseract and the CNN-LSTM model.
- Limited language support: The current system is trained only on English-language prescriptions and lacks support for regional or multilingual texts [16].
- Real-world variability: Factors like lighting conditions, scan orientation, and background noise in actual clinical settings may affect consistency. Further domain-specific fine-tuning and data augmentation are needed to improve robustness [17],[21].

Addressing these limitations will involve collecting more diverse training data, implementing domain-specific language models, and enhancing the preprocessing pipeline for adaptive real-time corrections.

6. CONCLUSION

The proposed AI-based system for interpreting handwritten medical prescriptions demonstrates the potential of deep learning in addressing real-world challenges in healthcare communication and documentation. By combining traditional OCR with CNN-LSTM architectures, the system successfully digitizes handwritten content with high accuracy and processing efficiency [1],[4],[17].

6.1 Summary of Results

The hybrid recognition system achieved an accuracy of over 90% on real-world handwritten prescription datasets [17]. With a character error rate under 8%, it demonstrated strong performance in interpreting a wide range of handwriting styles, including moderately cursive and stylized content.

The average processing time ranged between 1 to 2 seconds per image, making the solution viable for real-time use in clinics and pharmacies [20]. The use of Connectionist Temporal Classification (CTC) loss enabled the model to handle unsegmented sequences efficiently [1], while OpenCV-based preprocessing improved image clarity [10]. Tesseract OCR served as a fast, layout-aware first-pass recognizer whose output was refined by the deep learning model for higher precision and recall [2],[8].

These results confirm the system's effectiveness in improving prescription readability, reducing manual transcription efforts, and supporting digitization efforts in healthcare.

6.2 Key Takeaways

- The combination of OCR and deep learning models (CNN + LSTM) significantly enhances handwritten text recognition in medical prescriptions [4],[17].
- Image preprocessing techniques, such as grayscale conversion and noise removal, are essential for model robustness and accuracy [10].
- The system is modular, scalable, and suitable for real-time deployment in healthcare environments [17],[20].
- It lays the groundwork for future extensions such as multilingual support, mobile application deployment, and EHR integration [16],[21].
- Above all, this solution directly addresses a critical issue in healthcare—reducing transcription errors due to illegible handwriting, thereby improving patient safety and treatment efficiency [17].

7. FUTURE WORK

While the proposed system shows promising results in recognizing handwritten medical prescriptions, there is significant potential for enhancement and scalability. Future improvements aim to expand system functionality, improve recognition performance, and ensure widespread usability across diverse linguistic and clinical environments.

7.1 Enhancements

The following technical and functional enhancements are planned for future versions of the system:

- Integration with medical databases: By linking the output text to a medical drug database, the system can automatically fetch relevant information such as dosage, frequency, and contraindications [17].
- Spell correction and domain-specific language modeling: Implementing spell checkers and natural language processing (NLP) models specifically trained on medical terms will help reduce misinterpretation of handwritten or abbreviated content [20].
- User feedback integration: A feedback system where pharmacists or clinicians validate or correct outputs can help improve model accuracy over time through active learning [21].
- Mobile and offline deployment: Developing mobile applications or edge-compatible models can provide real-time assistance in rural and low-resource settings without requiring high-end infrastructure [16].
- Integration with Electronic Health Record (EHR) systems: Seamless integration of the recognized prescription data with hospital management systems can improve documentation workflows and patient safety [17].

7.2 Multilingual and Real-Time Deployment

To increase the utility of the system in diverse healthcare settings, multilingual and real-time capabilities are essential:

- Multilingual handwriting recognition: Future models will be extended to support prescriptions written in regional languages (e.g., Hindi, Marathi, Bengali) and global
- scripts by training on multilingual datasets and leveraging transfer learning techniques [16],[21].
- Real-time deployment: By deploying the model on GPU-enabled servers or cloud environments, it can provide near-instant recognition results, making it suitable for pharmacy counters and hospital reception desks [17].
- Edge deployment: Lightweight model versions can be created using model quantization or pruning to run efficiently on edge devices like tablets or kiosks for offline usage [20].
- These enhancements aim to transform the system into a robust, multilingual, and real-time prescription recognition solution for healthcare institutions of all sizes and region

8. ACKNOWLEDGMENTS

We would like to express our sincere gratitude to our project guide Prof. Sunita Parinam and co-guide Prof. Shailaja Rautrao from the Department of Computer Science and Engineering (Artificial Intelligence & Analytics), MIT Art, Design and Technology University, Pune, for their constant guidance, valuable suggestions, and encouragement throughout the project.

We also acknowledge the contributions of healthcare professionals and domain experts who assisted with the annotation of handwritten prescriptions, which was critical for the development and training of the system.

Our appreciation extends to the open-source communities behind TensorFlow, Tesseract OCR, and OpenCV for providing robust tools that enabled this research.

9. REFERENCES

[1] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, "Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks," *Proc. 23rd Int. Conf. on Machine Learning (ICML)*, pp. 369–376, 2006.

[2] R. Smith, "An Overview of the Tesseract OCR Engine," *Proc. 9th Int. Conf. Document Analysis and Recognition (ICDAR)*, vol. 2, pp. 629–633, 2007.

[3] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, 2017.

[4] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[5] T. Bluche, "Joint Line Segmentation and Transcription for End-to-End Handwritten Paragraph Recognition," *Neural Information Processing Systems (NeurIPS)*, vol. 29, 2016.

[6] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arXiv preprint*, arXiv:1409.1556, 2014.

[7] A. Vaswani et al., "Attention is All You Need," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017.

[8] Tesseract OCR, GitHub Repository. [Online]. Available: https://github.com/tesseract-ocr/tesseract

[9] TensorFlow, "An end-to-end open-source machine learning platform." [Online]. Available: https://www.tensorflow.org/

[10] OpenCV, "Open Source Computer Vision Library." [Online]. Available: https://opencv.org/

[11] A. Kharazmi, J. Puigcerver, A. Majumdar, and U.-V. Marti, "ICDAR 2019 Competition on Recognition of Handwritten Medical Forms," *Proc. 15th Int. Conf. Document Analysis and Recognition (ICDAR)*, pp. 1500–1505, 2019.

[12] M. Liwicki and H. Bunke, "IAM-OnDB – An On-Line English Sentence Database Acquired from Handwritten Text on a Whiteboard," *Proc. 8th Int. Conf. Document Analysis and Recognition (ICDAR)*, vol. 2, pp. 956–961, 2005.

[13] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.

[14] J. Schmidhuber, "Deep Learning in Neural Networks: An Overview," *Neural Networks*, vol. 61, pp. 85–117, 2015.

[15] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[16] G. Pavithiran et al., "Doctors Handwritten Prescription Recognition System in Multi Language Using Deep Learning," *arXiv preprint*, arXiv:2210.11666, 2022.

[17] U. Ali et al., "Leveraging Deep Learning with Multi-Head Attention for Accurate Extraction of Medicine from Handwritten Prescriptions," *arXiv preprint*, arXiv:2412.18199, 2024.

[18] V. Lobo, P. Sequeira, and A. Quadros, "Doctors' Handwriting Interpretation Using Deep Learning," *Proc. 3rd Int. Conf. on Optimization Techniques in Engineering (ICOFE-2024)*. [Online]. Available: https://ssrn.com/abstract=5091265

[19] T. Singh and B. Kaushik, "A Comprehensive Review on the Techniques Used for Recognising Handwritten Medical Prescriptions," *Proc. 7th Int. Conf. on Computing Sciences (ICCS 2023)*. [Online]. Available: https://ssrn.com/abstract=4490364

[20] A. Bhuyar, R. Khatale, and S. Jadhav, "Review on Doctor's Handwriting Recognition Using Deep Learning," *Int. J. Eng. Res. Technol. (IJERT)*, vol. 12, no. 3, pp. 428–434, 2023.

[21] T. Mankash, A. Gandhi, and P. Sarawgi, "MIRAGE: Multimodal Identification and Recognition of Annotations in Indian General Prescriptions," *arXiv preprint*, arXiv:2410.09729, 2024.