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Handwritten Medical Note Recognition Using NLP

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ABSTRACT
In the healthcare domain, illegible handwriting in medical prescriptions poses a significant challenge, often leading to errors in medication administration and delayed treatment. This project proposes a system that utilizes Optical Character Recognition (OCR) and Natural Language Processing (NLP) to automatically digitize and interpret handwritten medical notes. By integrating Tesseract OCR with Machine Learning techniques—specifically Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) models—the system effectively extracts textual content from complex handwritten inputs. Subsequently, NLP techniques, including Named Entity Recognition (NER) with BiLSTM and Conditional Random Fields (CRF), are employed to identify and structure critical medical information such as patient names, medications, dosages, and diagnoses. The proposed solution significantly improves the accuracy, efficiency, and automation of medical documentation, enabling better healthcare record management and reducing human error. Designed with scalability and usability in mind, this system represents a robust approach to modernizing healthcare data processing through intelligent document recognition and semantic analysis.

1-INTRODUCTION

Doctors typically write in incomprehensible handwriting, making it difficult for both the general public and some pharmacists to understand the medications they have prescribed. A study in Karnataka found that 18.3% of prescription errors were due to unreadable handwriting. This project addresses the issue using Optical Character Recognition (OCR) and Natural Language Processing (NLP). The system extracts handwritten text using OCR and ensures precise transcription, while NLP analyzes, structures, and categorizes the data. It also recognizes medical terms, abbreviations, and context-sensitive information, creating accurate digital records.

By automating the digitization of handwritten medical notes, the system significantly reduces human error and enhances the speed and reliability of medical documentation. It further aids in better patient care by making medical information easier to access, store, and analyze. The integration of deep learning techniques allows the system to adapt to different handwriting styles, making it robust and scalable for real-world healthcare environments.

2- LITERATURE SURVEY

1. Recognition of Doctors' Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation.(2021)

The paper suggests an online handwritten recognition system to identify doctors' handwriting and create a digital prescription using machine learning techniques. The study developed a primary "Handwritten Medical Term Corpus"dataset with 17,431 data samples comprising 480 words from 39 Bangladeshi doctors. On the preprocessed pictures, a new data augmentation technique called

SRP is used to increase the number of data samples. Following this, a sequence of line data is extracted from both the original and augmented image
data. Bidirectional LSTM is applied to the sequential line data derived from the augmented handwritten images to produce complete end-to-end recognition. The model achieved 73.4% accuracy without data expansion and 89.5% accuracy with
SRP data expansion

2. Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model(2021).
It is difficult to decipher a doctor's handwriting ona prescription. In this paper, they used neural network techniques such as CNN and BI-LSTM for predicting doctor's handwriting from medical prescriptions. The CTC loss function is used for normalization. This model builds on the IAM dataset. Image acquisition and data augmentation are used for image preprocessing. Furthermore, it is passed as input to 7 convolution layers of a neural network.32 training epochs were used by the training model, which took six hours to complete training and, on a graph, loss values are represented.

3. Medical Handwritten Prescription Recognition Using
CRNN.(2019)
The approach established a Convolutional Recurrent Neural Network (CRNN) technology using Python that can interpret handwritten English prescriptions and translate them into digital text. For this, datasets with 66 different classes, including alphanumeric characters, punctuation, and spaces,were used. Since prescriptions generally contain two or three words, the training was carried out using short texts. Normal handwriting and prescriptions from doctors were used to train the model. The system got a 98% accuracy rate after taking training time and data input into account. This paper further stated that in order to enhance the results, more work is needed on input handling techniques.

4. Intelligent Tool For Malayalam Cursive Handwritten Character Recognition Using Artificial Neural Network And Hidden Markov Model. (2017)
The approach uses the Hidden Markov Model (HMM) to recognise cursive handwritten Malayalam characters. By employing a median filter, the algorithm used here helps to avoid errors caused by noise in the scanned image.
Furthermore, Artificial Neural Network (ANN) aids in the acquisition of better classification and provides the best matching class for input. The samples used are of high quality in order to reduce the complexity of the recognition process.
This method yields better results in terms of speed and accuracy. As a result, the combination of both English and Malayalam characters can be recognised as a future work.

3- METHODOLOGY

Algorithms

1.Handwritten Text Recognition
(CNN + BiLSTM + CTC)

- CNN (Convolutional Neural Network):
  - Extracts spatial features from the handwritten image.
  - Captures patterns like strokes, edges, and shapes of characters.
  - Converts the image into a feature map.
- BiLSTM (Bidirectional Long Short-Term Memory):
  - Processes the feature map as a sequence.
  - Understands context in both directions (left-to-right and right-to-left).

- Learns dependencies between characters in handwritten words.

➢ CTC (Connectionist Temporal Classification) Loss:

- Decodes the output from BiLSTM into actual character sequences.
- Handles variable-length outputs without requiring character-level segmentation.
- Useful for unsegmented and messy handwriting.

2. Named Entity Recognition (NER)

➢ BiLSTM + CRF (Conditional Random Field):

- Takes the recognized text and tags key entities.
- Entities: Age, Medicine, Dosage, Symptoms, Instructions.
- CRF ensures optimal label sequences (avoids invalid tag combinations).

Step-by-Step Workflow of the Algorithm

PHASE 1: Image to Text

(OCR using CNN + BiLSTM + CTC)

➢ OCR using CNN

Step 1: Input Image

•Uploads the handwritten medical prescription

•It preprocess the uploaded image to the grayscale

Step 2: Convolution Operation

•Applies a set of learnable filters (kernels) to extract features like edges, curves, textures.

•Output: Feature maps.

Step 3: ReLU Activation

•Applies the ReLU function: $f(x) = \max(0, x)$Introduces non-linearity.

•So any negative values become 0, helping introduce non-linearity and removing negative activations.

Step 4: Pooling Layer (Max Pooling)

•Reduces spatial dimensions while keeping important features.

•Example: 2×2 max pooling → selects the max value in each 2x2 window.

STEP 5: Stack More Layers

•In real models, we stack:

•Multiple Conv → ReLU → Pooling blocks.

•Output is a sequence of feature vectors for text lines or columns.

STEP 6: Pass to BiLSTM

•Output of CNN is now a sequence of features per image column, perfect for feeding into BiLSTM for character-level prediction.

BILSTM ALGORITHM step by step

Let the input sequence from CNN be:

$X = [x_1, x_2, ..., x_n]$

where each x_i is a feature vector for a patch of the handwritten image.

Step 1: Initialization

Initialize the following for both forward and backward LSTMs:

•Hidden state $h_0 = 0$

•Cell state $c_0 = 0$

Step 2: Forward LSTM Pass

For each time step t = 1 to n, compute

Step 3: Backward LSTM Pass

•Now process the sequence in reverse:

From x_n to x_1, using a similar LSTM logic.

Step 4: Combine Outputs

•At each time step t, concatenate forward and backward hidden states:

$h_t\_final = [h_t\_forward ; h_t\_backward]$

•This combined representation contains both past and future context, which is crucial for recognizing ambiguous handwriting.

➢ Step-by-Step Flow of CTC Algorithm

Step 1: Input from BiLSTM

•The BiLSTM outputs a sequence of probability distributions over a character set

Step 2: Probability Table (Numerical Example)

Gives the probability of timesteps.

Step 3: Best Path Decoding (Greedy Decoding)

•At each timestep, choose the character with the highest probability:

T1: B (0.6)

T2: A (0.7)

T3: C (0.7)

T4: A (0.6)

•Best Path: B → A → C

Step 4: Remove Repeated Characters

If a character repeats (like: AA A), keep only one unless a blank separates them.

In our case:

B → A → C — no repeats → No change.

Step 5:Remove Blanks

•CTC uses blank as a placeholder — it's not part of the output.

•Here, we had no blanks selected → So final result remains:

Final Decoded Output:

BACA

➢ Phase 2: Medical Text Understanding (BiLSTM + CRF for NER)

Step 1: Text Preprocessing

•Tokenize the recognized text.

•Clean text (remove special characters, lowercasing, etc).

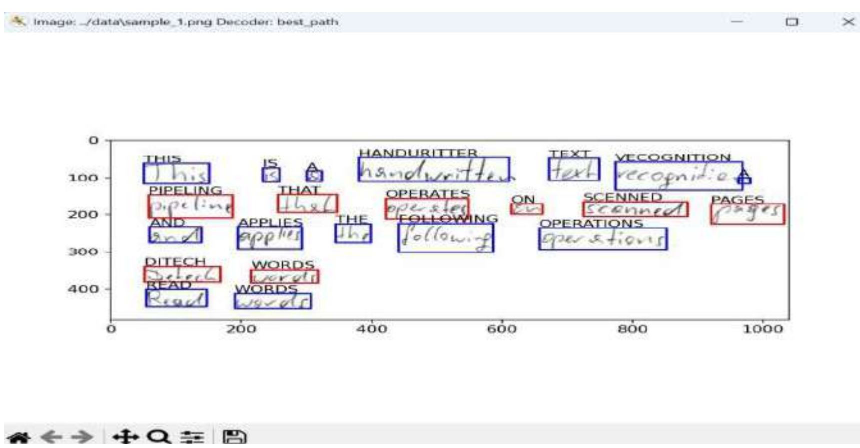
Step 2: Named Entity Recognition using BiLSTM + CRF

•Convert tokens to word embeddings (e.g., GloVe, Word2Vec).

•Feed embeddings into BiLSTM to capture contextual word meaning.

•Use a CRF layer on top to label each token

4-RESULT



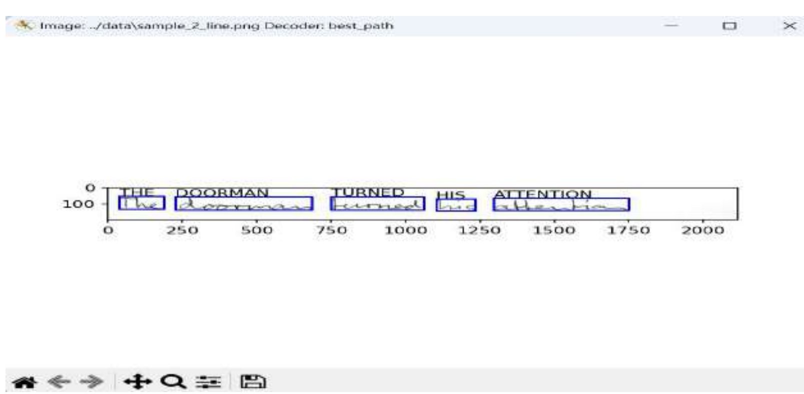


Fig-1 Trained example image

Fig-2 Trained example image

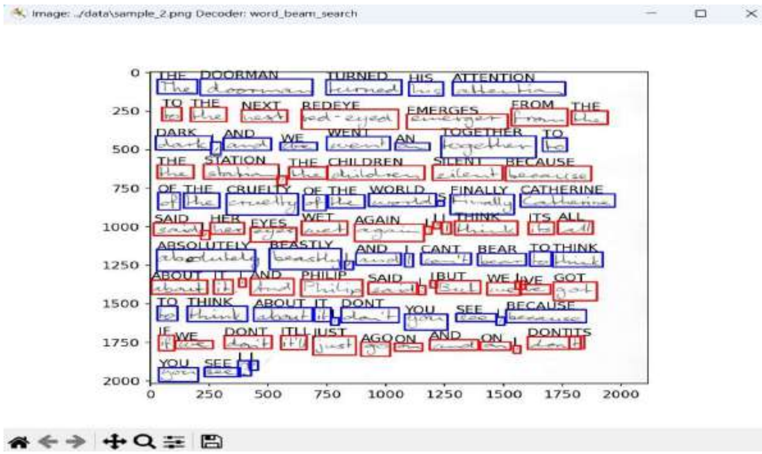


Fig- 3 Trained example image

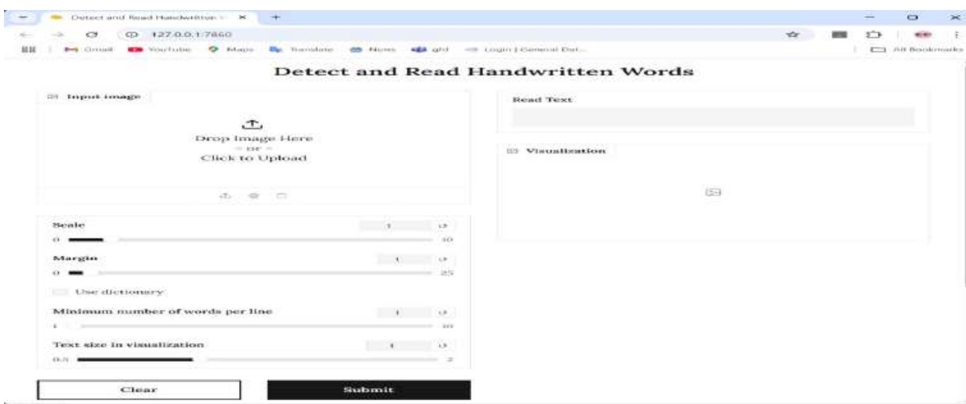


Fig-4 Upon running the application, The web application will open. Go to the click file

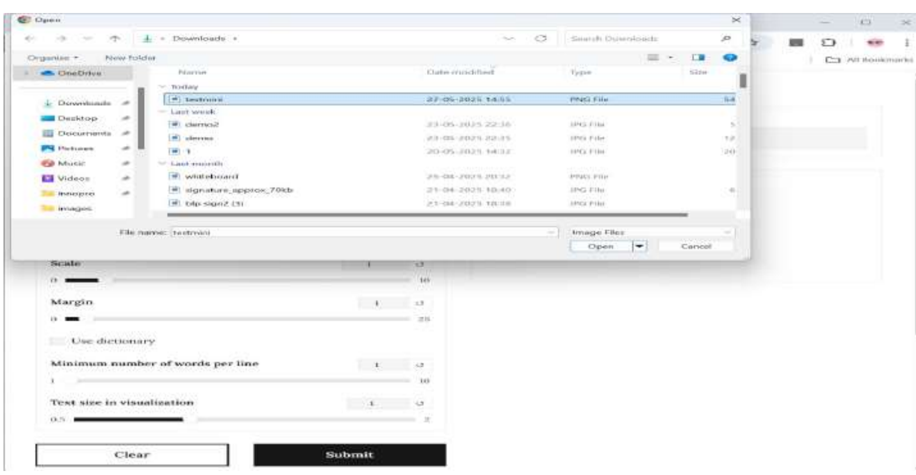


Fig-5 Select the jpg /png image option from your computer

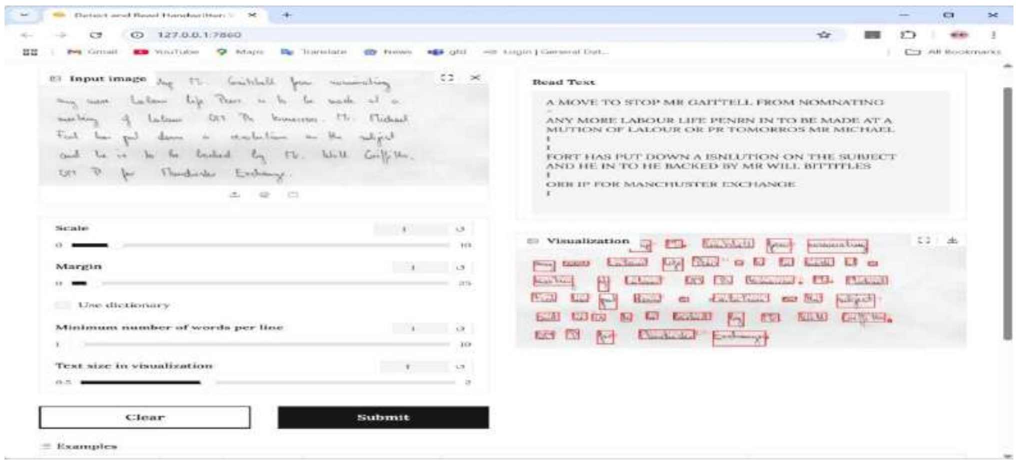


Fig- 6 Result after uploading the image

5- CONCLUSION & FUTURE SCOPE

CONCLUSION

The Handwritten Medical Note Recognition system helps digitize handwritten prescriptions, making healthcare documentation more accurate, efficient, and organized. It reduces the errors caused by illegible handwriting and saves time for both doctors and administrative staff. By using OCR and NLP techniques, the system can automatically read, understand, and extract key medical details like patient name, medicine, dosage, and symptoms. In today's digital age, automating this process is not just helpful—it is essential for improving the quality of healthcare services and ensuring better patient safety.

In future, Real-Time Integration with EHR Systems: Connect with electronic health record systems to automatically update patient records with extracted prescription data. Support for Multi-Language Prescriptions: Expand the system to recognize handwritten notes written in regional or multiple languages for wider usability.

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