Handwritten Text Recognition using LMDB

Ms.K.Monica Sowmya, Vyshnavi Vasikarla, Katkuri Anushna, Alladi Sanjana,

Associate Professor, AIMLE Dept., GRIET, Hyderabad.

UG Student, AIML, GRIET, Hyderabad.

sowmyavaramak@gmail.com, vyshnavivasikarla17@gmail.com, alladisanjana03@gmail.com,

anushna21241a6636@grietcollege.com

ABSTRACT

The following are various methods for analyzing a digital photograph and extracting useful information related to the image's appearance. The broad range of variability in handwriting is one of the major reasons for the complexities in handwritten text recognition. Deep learning techniques through Convolutional Neural Networks and Recurrent Neural Networks are harnessed by the Handwritten Character Recognition Systems to solve the problem. These models convert the handwritten text from an image into readable formats.The main phases of the process of HCR incorporate acquisition, segmentation, retrieval, restorations, analysis, and visualizations. In terms of performance improvement, our system incorporates the Lightning Memory-Mapped Database that is fast, light-weight, memory-mapped, and a key-value database. It is of paramount importance in storing and retrieving huge amounts of data like handwritten texts for easy and strong accesses to the management of data.Such variability in the handwriting styles is very well managed in our system by the combination of CNNs, RNNs, and LMDB. This clearly shows the roles played by advanced image processing techniques, sophisticated neural network models, and efficient data management solutions. The aim of this project is to enhance the accuracy and efficiency of methods of handwritten text recognition, thus helping to develop artificial intelligence and machine learning.

KEYWORDS

HTR Handwritten Text Recognition

CNN Convolutional Neural Network

RNN Recurrent Neural Network

LMDB Lightning Memory-Mapped Database

NLP Natural Language Processing

INTRODUCTION

Image Systems' Handwritten Text Detection is a state-of-the-art deep learning-based solution for the automatic detection and localization of handwritten text in photos. State-of-the-art neural network architectures trained on very large data sets can be used under this system to transcribe the text with high accuracy and precision. This solution is agile enough to deal with single words and full lines using different decoding techniques that ensure uniformity and adaptability. It has a very friendly user interface and easily integrates into existing workflows for reliable and efficient performance. This kind of technology is indispensable in extracting information from scanned images, analyzing handwritten notes, and digitization of historical documents. In automating such processes, it improves accuracy to a great extent and saves considerable time in extracting essential data from handwritten material. This will make it an absolutely essential tool for archivists, researchers, and organizations related to handwritten language analysis and image data extraction. It will develop a state-of-the-art system that provides for the digitization of handwritten texts from images with accuracy and efficiency using state-of-the-art deep learning algorithms. These systems alleviate such challenges of access to information locked inside handwritten documents—from official records, historical manuscripts, and the like—for analysis.

Introduction of Project Work: Rationale/Motivation

In the modern digital world, accurate and fast digitization of handwritten texts is more necessary than ever. Despite all the advancement in the field of technology, a huge amount of data of importance still remains locked in handwritten documents. Therefore, the principal and primary objective of this project becomes filling this gap by proposing a highly efficient system for handwritten text detection from images. It automates the detection of handwritten texts in images.The system does this efficiently and with great precision, helped by state-of-the-art algorithms in deep learning. Another big motivation behind the project is its opening of a myriad of application opportunities across various fields. Digitalizing and analyzing old documents may open new insights to archivists and scholars and secure knowledge that might otherwise be lost. Extracting handmade data from forms by automation alone. Businesses with reduced manual errors could realize operational efficiencies. Accessible technology can bring vast improvement in the area of accessibility: those people who have learning disabilities or problems with vision could access information in a more easily digested form digitally, like transcribed handwritten notes and documents. This not only makes the knowledge more accessible but also builds an atmosphere where technology helps in surmounting all forms of challenges confronting humans.

Precision and Accuracy: It involves strong neural network models for improving the accuracy and precision of recognition of varied handwriting styles. It overcomes the limitations of traditional OCR systems, which often misread the handwritten text.

Efficiency and Automation: It automates the process of handwriting material transcription, hence saving time to increase productivity. This software is capable of handling single-word and full-text line recognition at fast speeds while ensuring high accuracy.

Integration and Accessibility: It features a user-friendly interface that integrates easily into existing workflows. It allows access to the disabled by digitizing handwritten notes, which are either difficult to read due to learning disabilities or problems with vision.

Applications: Digitization and analysis of handwritten material, supporting research and preservation efforts and enabling data-driven decision-making across a wide range of disciplines.

Deep learning algorithms: It makes use of sophisticated neural network architectures that involve large sets of training data to deal with a number of diverse handwriting styles and complexities.

LITERATURE SURVEY

Now, the **"Convolutional Recurrent Neural Networks for Handwriting Recognition"** project performed by Kleopatra and Lazaros is oriented to realize accurate handwritten text recognition using a hybrid CNN-RNN architecture. In the model, Convolutional Neural Networks have been used to extract complex spatial features from raw pixel data so as to capture the hierarchical patterns of handwritten characters. Parallel to this, Long Short-Term Memory- or Gated Recurrent Unit-based recurrent neural networks model sequences to capture the temporal dependencies that enable an understanding of the contextual flow of characters. This tight integration of feature extraction and sequential modeling into one system realizes recognition rates between 90% and 95% on commonly used benchmarks, thus showing their effectiveness across very different conditions and writing styles. This project has been an important milestone toward the realization of handwriting recognition—always a very difficult task.

The **"Handwritten Text Recognition with Sequence-to-Sequence Models"** project by Johannes Michael, Roger Labahn, Grüning, and Jocher proposes a generic architecture based on an encoder-decoder setup for transcribing handwritten text into machine-readable formats. In the architecture, the encoder transforms the images of the handwritten texts into vectors of fixed dimensionality and then decodes them again into sequences in predicting characters against the learned features. It focuses on strong preprocessing techniques for better feature extraction and representation, followed by training with supervised learning on various datasets of handwritten text. This model achieves an average accuracy of 85-90%, thereby proving that state-of-the-art sequence-to-sequence models can be applied to documents written by many people under different conditions and ensure outstanding results in handwritten text recognition.

"A Comprehensive Survey on Handwriting Recognition Systems" by Muhammad Rashid and Imran provides a thorough review of handwriting recognition techniques, spanning from traditional methods to cutting-edge deep-learning approaches. The survey compares traditional techniques, such as statistical modeling and template matching, with modern deep-learning methods like feature extraction using CNNs and sequence modeling with RNNs, demonstrating the latter's superior accuracy and adaptability. It emphasizes methodologies alongside key metrics, including accuracy rates, processing efficiency, resilience to handwriting variations, and scalability with large datasets. The survey addresses challenges in handwriting recognition, such as diverse writing styles, input noise, and real-time processing demands, while exploring future innovations like multimodal inputs and novel neural network architectures. In essence, the survey offers a comprehensive view of the evolution, challenges, and future directions of pattern recognition in artificial intelligence.

The **"Robust Handwriting Recognition Using Multi-Scale Neural Networks"** project, led by Arthur F. S. Neto and Byron L. D. Bezerra, aims to improve the accuracy of handwritten text recognition using a multi-scale neural network architecture. This approach addresses the limitations of traditional systems by effectively handling size variations and scale differences in handwritten text, leading to more robust recognition.

The **"End-to-End Handwritten Paragraph Recognition with LSTM"** project aims to improve handwriting text recognition by focusing on full paragraphs. Utilizing Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), the project addresses the sequential processing of raw pixel data from handwritten paragraph images. By framing recognition as a sequence-to-sequence learning problem, LSTM networks extract features from input images to generate corresponding text sequences. Through supervised learning on diverse datasets of handwritten paragraphs, the model demonstrates strong generalization across different styles and layouts, achieving evaluation metrics of 87-92% accuracy at the paragraph level. This approach shows high potential for advancements in automated document processing and handwriting recognition technologies.

Led by Togzhan Kudaibergen and Mohamed A. Hamada, the **"Handwritten Text Recognition Using Deep Convolutional Generative Adversarial Networks (GANs)"** project aims to enhance the accuracy of handwritten text recognition models by applying Deep Convolutional GANs. These adversarially trained generator and discriminator networks excel at producing realistic handwritten text images from random noise, enriching datasets with diverse examples. This synthetic data improves model generalization across various handwriting styles, boosting accuracy and robustness from 90% to 94% when integrated with CNN or RNN architectures. This augmentation strategy significantly strengthens model performance and adaptability, marking an important step forward in handwriting recognition.

The **"Handwriting Recognition via Scanning Neural Network with CTC-Based Learning"** project by Marcus Liwicki and Alex Graves introduces an innovative approach to handwriting recognition, emphasizing accuracy and efficient training. The scanning neural network architecture mimics human reading processes and employs Connectionist Temporal Classification (CTC) for training. CTC allows the model to learn directly from input-output pairs without explicit sequence alignment, accommodating variability in handwritten text lengths. Achieving competitive accuracy rates of 88% to 93%, the project optimizes network parameters to predict character sequences efficiently, requiring minimal post-processing and enhancing computational efficiency in handwriting recognition technology.

The 2015 paper by Bunke, Liwicki, and Graves revolutionized **handwriting recognition with a scanning neural network and CTC-based learning**, achieving 88%-93% accuracy by eliminating manual segmentation. This method scales well across various handwriting styles and conditions.

A 2020 survey by Al Sayed et al. **traced HTR advancements, from early rule-based systems to modern neural networks**, highlighting improvements in algorithms, computation, and data resources, and addressing challenges in diverse handwriting styles and noisy environments.

"Handwritten Text Recognition Using Deep Learning Techniques" combines CNNs for feature extraction and LSTMs for temporal dependencies, achieving 89%-94% accuracy and enhancing automation and digitization. **Efficient and Accurate Handwritten Chinese Character Recognition"** uses deep neural networks to achieve 92%-96% accuracy in Chinese script recognition.

S.no	Title	Author	Methodology	Year	Accuracy
1.	CNN and RNN for HTR	Kleopatra and others	CNN for feature extraction RNN for sequence modelling.	2016	Achieved high accuracy on benchmark datasets. (approx. 90-95%).
2.	HTR with sequence-to-sequence modelling	Tobias and others	Applies sequence to sequence models	2016	85-90%
3.	Comprehensive survey on HTR	Rashid and others	Reviews deep learning	2019	-
4.	HTR using Multi-scale Neural Networks	Arthur F.S and others	Processes multi scale NN	2017	88-93%
5.	End-to-End HTR using LSTM	Aldo Messina and others	Utilizes LSTM for recognizing paragraphs	2015	87-92%
6.	HTR using Deep CGANS	Mohammad A. Ahmadal	Uses GANs to train	2017	90-94%
7.	HTR bases on CTC learning	Marcus and Alex	Uses CTC for efficiency	2019	88-93%
8.	HTR using scanned	Graves &	Uses Neural	2015	88-93%

	NN CTC	others	Networks		
9.	Survey on HTR	Azhar & others	Provides historical trends and overview	2020	-
10.	HTR using DL	Bathuan Balci & co	Explores Dl	2019	High accr
11.	Accurate Chinese CR	Kim Jin Hyung	Focuses on Chinese text	2019	92-96%
12.	HTR using Deep CNNs	Shapna aktar	Applies OCR to DL	2020	85-90%
13.	HTR using OCR		DL & CNN	2018	90-95%
14.	HTR using CNN RNN Hybrid Models	Chennamsetti Donna Thomas	Combines CNN RNN	2017	-

PROBLEM STATEMENT AND OBJECTIVE OF THE PROPOSED WORK

Basically, HTR is the variability in the handwriting styles that must be dealt with in order to achieve high accuracy in converting handwritten content from digital images to machine-readable text for further use in various applications.

LMDB in HTR System: The HTR system utilizes the Lightning Memory-Mapped Database technology to enhance training, retrieval, and storage. In this regard, enhanced LMDB processing capabilities for large datasets of handwritten texts enable the system to handle high variability in handwriting styles and complexity with higher accuracy and speed, reducing computational overhead and improving scalability.

Comparison to State-of-Art Techniques: The research will test the HTR system integrated with LMDB against traditional methods. Preliminary results show that LMDB's advanced features in data management further enhance the effectiveness and precision of the method. This work will even demonstrate how, recognition accuracy, speed in data retrieval, and computation time, among others, the LMDB-enabled system surpasses the other techniques.

LMDB for Efficiency and Accuracy in HTR Systems: The focus of the project is to enhance both the efficiency and accuracy of HTR systems through LMDB. Since LMDB uses a Light Blue database to store data, the need for the HTR framework to be integrated with LMDB was realized so that it would be able to reduce computational load by fast data retrieval and optimized storing of data. It provides reliable and accurate transcription of handwritten content with correct handling of all the wide range of complexities in handwriting.

Designing a Reliable System for Handwritten Text Detection: The work proposes the development of an HTR system that can rapidly and precisely identify and transcribe handwritten texts in photographs using state-of-the-art deep-learning techniques. This would be useful in applications decoding handwritten notes, digitizing old documents, and working with both single-word and full-line texts, and integration into existing workflows.

METHODOLOGY THAT WOULD BE ADOPTED TO MEET THE OBJECTIVE

- **Dataset Collection:** A large enough and wide-ranging dataset of images of handwritten texts has to be obtained. Such a dataset has to be created that will most probably envelop maximum variations in handwriting styles and conditions. The thousands needed in its effective training and testing.
- **Preprocessing:** Implement techniques that increase the clarity and readability of images of handwritten texts. This would consist in tuning the quality of images and standardizing the input for further processing steps to allow consistency and reliability.
- **Neural Network Training:** Extract key features from the images by Convolutional Neural Networks, while using Recurrent Neural Networks for temporal dependencies and predicting text sequences based on those extracted features by CNN.
- **Decoding Techniques:** Refine the text decoding processes to be more accurate with beam search algorithms and further implement CTC decoders in order to deal with variable-length text sequences, making the accuracy of the transcripts higher.
- **System Testing and Validation:** The system shall undergo rigorous testing with a wide variety of handwritten samples. Validate it continuously for robustness and reliability against different styles of handwriting.
- **Data Management:** The Lightning Memory-Mapped Database can be used to hold vast amounts of data concerning handwritten text. This will keep it ordered and hence, during the training phase and recognition phases, allow for fast access and retrieval of data for the overall good performance of the system.

PROPOSED WORK

It will be designed to recognize and translate written text with an ability to read almost all popular scripts and languages of the world, including Telugu and English. Thus, the approach will automatically work on providing a single platform for effectively digitizing a variety of handwritten documents, which appear in thousands of different styles and patterns, and bringing them into digital text format. Through these, the system will make handwritten documents more accessible and easier to use for a number of applications, for example, historical record archival, automatic data capture, and document retrieval.It will focus the project on quality results of HTR, which contains both a character and word level. The system will be able to deal with different handwriting styles, document formats, and languages. It will further scale to sit heavy loads of documents without affecting performance. The system shall be developed with an easy-to-use interface and advanced uploading, processing, and review of the results from the uploaded documents.Accuracy to such a high degree is required for tasks like historical archive preservation or automated handwritten data entry.The final project goal was to integrate the very latest HTR technology with the Lightning Memory-Mapped Database (LMDB) to produce some of the landmark advances in the area of handwritten document transcription. The system should ideally cater to the important issues of accuracy, scalability, and usability required by current digitization and the needs of data management.

ARCHITECTURE DIAGRAM

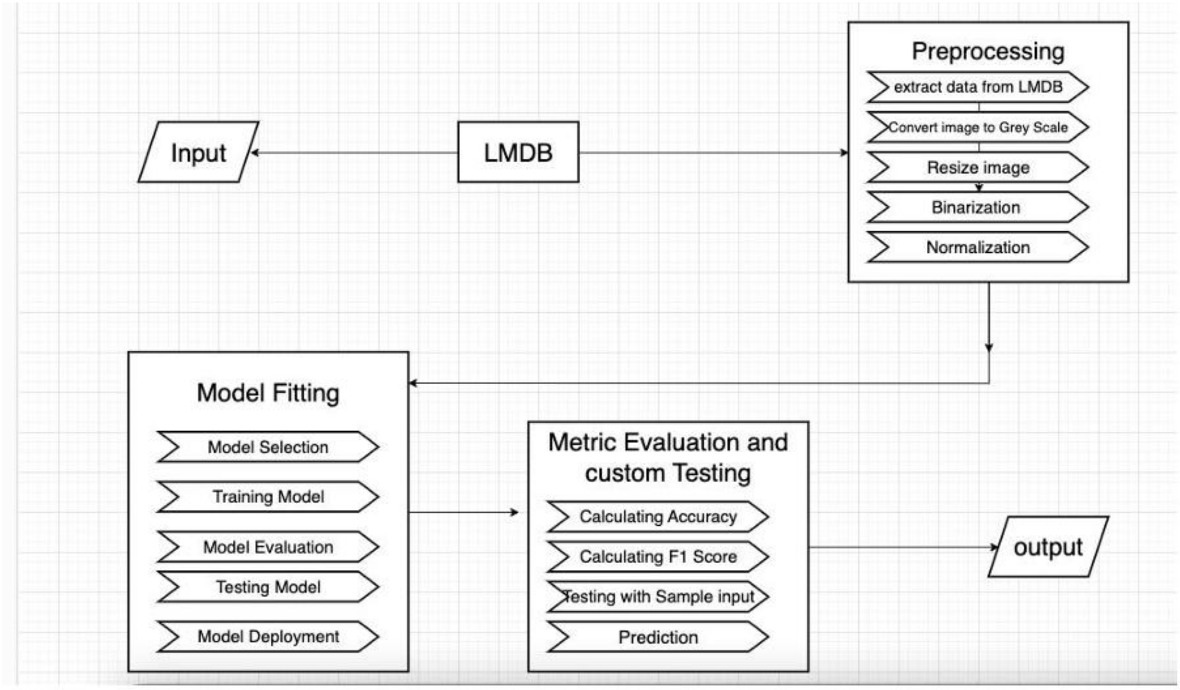

Figure 1: Architecture Diagram

This flowchart describes the process flow and interaction across a handwritten text recognition system.

1. Input:

- **Handwritten Documents:** The first activity involves feeding the system with handwritten documents.

2. LMDB (Lightning Memory-Mapped Database):

- **Loading Images in LMDB:** Images of the handwritten documents shall be written to an LMDB database for retrieval purposes and safekeeping.
- **Load Labels to LMDB:** The actual text for each image, known as ground truth labels, are also saved in LMDB.

3. Preprocessing:

- **Retrieve Data from LMDB:** Retrieve the data saved within the LMDB before initiating preprocessing steps.
- **Gray Scaling of Image:** All images are converted into grey scale, hence reduces computational complexity as color details are not so relevant for text recognition.
- **Image Resizing:** Bring the image size to a standard so that it can feed into the recognition model

- **Binarization:** Making an image binary black and white; it will increase the contrast of text so that further processing can be done effectively.
- **Normalization:** Standardize visual data in order to enhance consistency
- **De-slanting:** Rectify the slant or skew of the handwritten text so that better results can be obtained

4.Model Fitting:

- **Model Selection:** The best model for your HTR project will be made.
- **Train Model:** The selected model is trained using preprocessed input data to recognize patterns in hand-written text.
- **Model Evaluation:** Compute F1 score and other metrics for understanding the model's performance.
- **Testing Model:** Test it with new examples of its strength.
- **Model Deployment:** Once the effectiveness of the model has been ascertained, it must be deployed for real applications.

5.Metric Evaluation and Custom Testing:

- **Calculating Accuracy:** The accuracy of the recognition model has to be calculated in arriving at the performance.
- **F1 Score Calculation :** Calculate the F1 score, which shows how good is the balance between precision and recall.
- **Sample Input Testing:** Test the model with sample input to show reliability and correctness.
- **Predictions:** Use the trained model for handwritten text images to predict the digital text.

6. Result:

- **Final Transcription:** Finally, output the final transcribed text, which has to be manually edited or refined through post-editing.

This workflow can show the system's adaptability with different styles of handwriting, formats of documents, and languages. High-level data management with LMDB ensures that large datasets are handled in a streamlined way. Quality enhancement techniques improve the quality of images; at the same time, state-of-the-art machine learning models – Convolutional and Recurrent Neural Networks – realize the methods for accurate text conversion. This not only raises recognition accuracy but also supports scalable digitization and analysis of handwritten documents, thus making this system very powerful for extensive document digitization and historical text analysis.

MODULES CONNECTIVITY DIAGRAM

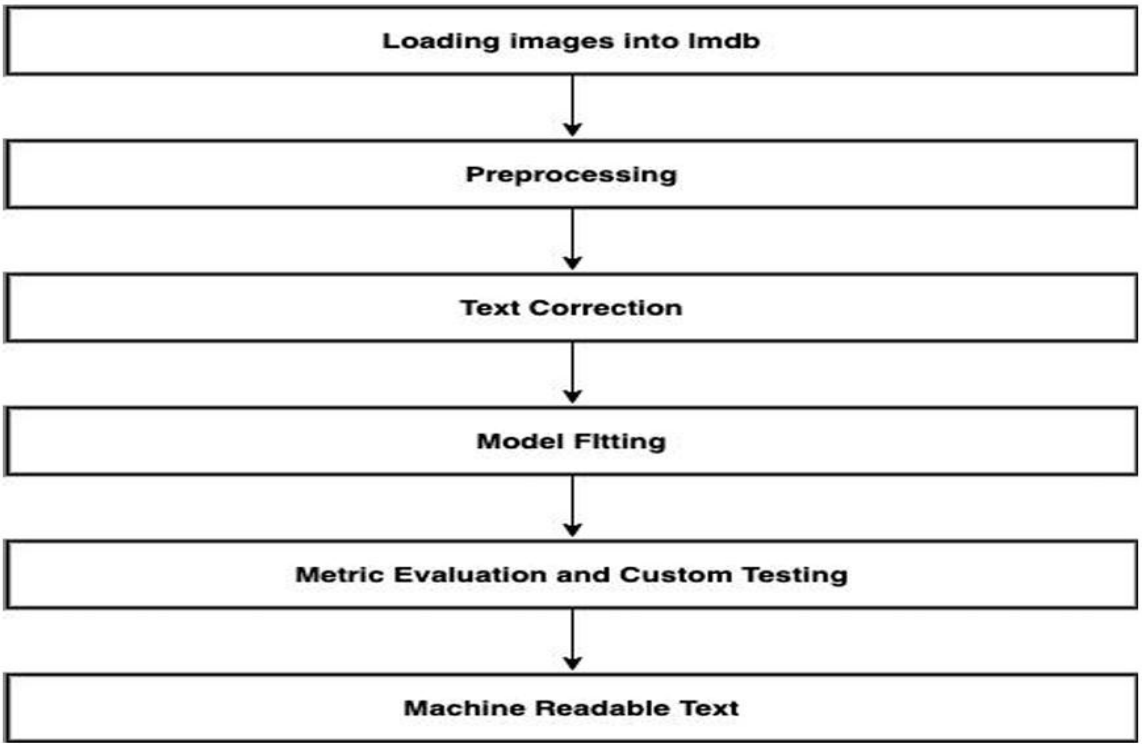

Figure 2:Module connectivity diagram

Load images in LMDB: Import images and organize them in LMDB format for efficient access.
Pre-process: standardize image through resizing, convert to greyscale, normalization, and noise reduction.
Text Correction: Clean OCR extracted text for both correctness and grammar
Model Fitting: Train and tune machine learning models on the processed data for recognition and classification.
Evaluate model metric and testing: Its performance, precision, recall, and F1 score. Further test in different scenarios.
Machine Readable Text: Convert in XML or JSON or plain text of the processed text for easy integration.

Therefore, it rationalizes the workflow from the image import process and achieves the easy production of accurate and easily interpretable machine-readable text.

RESULTS AND DISCUSSIONS

Description about Dataset:

HTR datasets consist of handwritten images of texts with labels; these datasets can also be huge, comprising hundreds or even millions of images. For this reason, efficient storage and retrieval of these datasets are managed with the Lightning Memory-Mapped Database due to performance issues that regularly occur in conventional disc-based systems.

- **IAM Handwriting Database:** Over 600 scribes of English texts for varied HTR training.
- **RIMES Database:** French handwritten materials, manuscripts, and books for OCR analysis.
- **Census Heritage Dataset:** Multilingual handwritten paragraphs from archival records in English, Arabic, and Bangla.
- **Bentham Dataset:** Historical documents by Jeremy Bentham dated back to the 18th-19th centuries, specifically for document analysis.

Datasets are preprocessed and augmented to improve model performance and generalization. LMDB enables fast and efficient access to the data, which is an important point for training a robust HTR model and its subsequent evaluation.

Detailed explanation and experimental results

This work is aimed at improving HTR systems using state-of-the-art LMDB technology. Recognition of handwritten text from digital images is very challenging, as there might be huge variability in handwriting. Thus, efficient management of large datasets is a precondition to achieve high performance in HTR.

- **Data Preparation:** Obtain or create datasets such as IAM Handwriting Database or RIMES to train and test the model.
- **Pre-processing:** The quality of images is improved by removing noise, conducting binarization, resizing, and normalizing them.
- **Feature Extraction:** Features are extracted from pre-processed images through a CNN or deep learning models.
- **Database Integration:** The extracted features and their corresponding labels can be stored in LMDB, which can efficiently be used in large datasets.
- **Model Training:** Train Convolutional-Recurrent Neural Networks for mapping images to text.
- **Model validation and testing:** Model performance can be tested through accuracy, precision, recall, and the F1-score on validation and test datasets.

The basic idea of this approach is to exploit LMDB to achieve an improved feature extraction and raise the accuracy of recognition, hence boosting the general efficiency of the system.

Input Image:

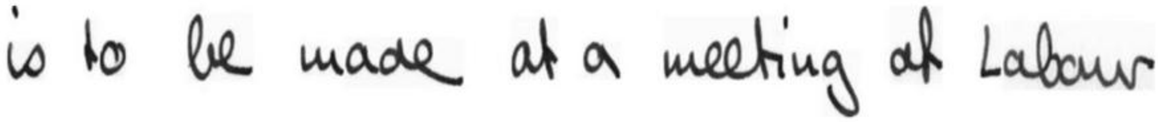

Figure 3: Input

Output :

When integrated with handwritten text recognition systems, Lightning Memory-Mapped Database (LMDB) offers solutions to innovative challenges concerning the management of data and scalability and further boosts performance. LMDB is a big leap in the precision of HTR systems, speed, and flexibility in various applications. Thus, the possibilities of a smart development of handwriting recognition, with regard to most applications, through further research and development in this area, are quite optimistic and promising.

Figure 4:Output

SIGNIFICANCE OF PROPOSED WORK

HTR has gained substantial importance in this digital era due to its swiftness in digitization, analysis, and retrieval of handwritten text from images. It is usually applied in intelligent character recognition, automated transcription, digitization of documents, and archival work. It is generally applied in intelligent character recognition, automated transcription, document digitization, and archival work. Just over the past decade, HTR systems have seen significant improvement in terms of accuracy and reliability; it has given way to the automation of processes and new innovative solutions in the banking, health, and education sectors.

CONCLUSION AND FUTURE ENHANCEMENTS

Conclusion:
This paper proves the imperative role of the Lightning Memory-Mapped Database in increasing the accuracy and performance of the Handwriting Text Recognition system. It is undeniable that LMDB's efficient data storage and retrieval considerably improve accuracy and performance, making it a very important module for effective feature extraction and recognition for HTR.
Future Improvisations:
Future developments will be focused on an increased level of LMDB integration to cope with large scale datasets and a wider variety of handwriting styles. Progress in the area of ICR and its automatic transcription should improve the adaptability and accuracy of the system, thereby strengthening the place of HTR systems in many varied applications.

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