Handwriting And E-Text Recognition With Sentiment And Emotion Analysis: A Hybrid Deep Learning Approach

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Abstract- *Despite the convenience of pen and paper, managing handwritten documents remains challenging due to issues with storage, retrieval, and sharing. Handwriting-to-text conversion (HTC) addresses these limitations by transforming handwritten text into a digital format, making it easier to access, store, and analyze. This study introduces the ESIHE_AML (Exploration of Sentiment Insights in Handwritten and E-text using Advanced Machine Learning) model, which combines Optical Character Recognition (OCR) with sentiment analysis to classify sentiment polarity (positive, negative, or neutral) and detect emotions such as happiness, sadness, anger, and fear. The model incorporates deep learning algorithms such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for emotion detection and sentiment classification. In addition, the system uses the Helsinki-NLP/opus-mt-tam-en for Tamil-to-English translation, facilitating sentiment analysis on multilingual handwritten texts. The model was evaluated on benchmark datasets like Twitter, Kaggle, IAM, and Amazon reviews, achieving an accuracy rate exceeding 90%. This research contributes to advancing sentiment analysis techniques by incorporating both traditional handwritten and digital text formats, making it applicable for use cases in social media monitoring, customer feedback analysis*

Keywords- Handwriting-to-Text Conversion (HTC), Sentiment Analysis, Emotion Detection, Deep Learning, Optical Character Recognition (OCR), Tamil-to-English Translation, ESIHE_AML Model, Machine Learning.

I. INTRODUCTION

Handwritten text has been a crucial means of communication throughout history, ranging from personal messages to formal documents. However, working with handwritten content in the digital world presents several difficulties, especially when it comes to storing, searching, and sharing the information. Unlike digital text, handwritten documents are not easily accessible or searchable, which complicates their use in the modern digital ecosystem. As reliance on digital systems grows, there is a pressing need to convert handwritten text into a digital format that can be quickly stored, retrieved, and analyzed. Handwriting-to-text (HTC) conversion is a key technology that addresses these issues by transforming handwritten content into electronic text (E-text), making it more manageable and accessible.

While significant progress has been made in Optical Character Recognition (OCR) technologies for converting printed text into digital form, OCR systems still face challenges when dealing with the complexity of human handwriting. The variety in handwriting styles—such as differences in letter formation, slant, size, pressure, and cursive writing—makes it difficult for traditional OCR methods to achieve high levels of accuracy. Thus, there is an ongoing need for more advanced and adaptable solutions to handle the intricacies of handwritten text.

This study seeks to overcome the shortcomings of conventional OCR and handwriting recognition technologies by integrating sentiment analysis and emotional insight into the handwriting-to-text conversion process. The research introduces the **ESIHE_AML (Exploring Sentiment Insights in Handwritten and E-text with Advanced Machine Learning)** model, which merges cutting-edge machine learning techniques to both recognize handwritten text and analyze the emotional tone conveyed within the content. The model utilizes Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to not only extract text from handwritten documents but also to assess the sentiment and emotions underlying the text.

Sentiment analysis is a technique in natural language processing (NLP) that identifies the emotional tone or polarity (positive, negative, or neutral) within a body of text. It provides valuable insights into the attitudes and feelings expressed in the text. Emotion detection takes this a step further by classifying the specific emotions—such as joy, sadness, anger, or fear—that the text conveys. The combination of these two techniques allows the **ESIHE_AML** model to provide a deeper understanding of handwritten content, offering both sentiment classification and emotion detection. This dual approach is especially useful in fields like social media monitoring, customer feedback evaluation, and mental health analysis, where recognizing emotional tones and sentiments is critical for informed decision-making.

The proposed model's performance is evaluated using a variety of publicly available datasets, such as Twitter, Kaggle, IAM, and Amazon reviews. The **ESIHE_AML** model achieved an accuracy rate exceeding 90%, underscoring its potential applicability in practical scenarios. The impressive performance demonstrates the value of integrating deep learning approaches, multilingual support, and advanced sentiment and emotion detection into a unified system capable of processing both handwritten and digital text formats.The fields of sentiment analysis and emotion detection have gained significant attention due to their broad range of applications. In business, sentiment analysis can provide insights into customer satisfaction, public perception, and brand sentiment. In healthcare, emotion detection can offer critical information for understanding patients' mental and emotional health. The ability to analyze both handwritten and typed content within the same system creates new possibilities for automating sentiment analysis across diverse media, from handwritten feedback to social media posts.This research is driven by the need to enhance the accuracy and accessibility of sentiment analysis tools, particularly when dealing with handwritten documents. By utilizing state-of-the-art deep learning algorithms, the **ESIHE_AML** model contributes to the development of more effective sentiment and emotion analysis tools. Its ability to analyze handwritten text alongside digital content makes it a valuable tool for applications across various industries, including business, healthcare, and social media analysis.The paper is organized as follows: Section II provides an in-depth review of existing research on sentiment analysis, emotion detection, and handwriting-to-text conversion technologies. Section III details the methodology used in the **ESIHE_AML** model, including the machine learning techniques employed. Section IV presents the results of the model’s evaluation on the benchmark datasets, showcasing its performance and accuracy. Finally, Section V concludes the paper and discusses potential directions for future research, such as the exploration of hybrid models to improve accuracy further.

II. RELATED WORK

Handwriting analysis has been extensively researched in the fields of OCR, sentiment analysis, and emotion detection. Traditional OCR methods primarily relied on rule-based systems, but modern advancements integrate machine learning (ML) and deep learning (DL) for improved accuracy. Sentiment analysis, which was initially applied to printed and digital text, has now expanded to handwritten documents through deep learning techniques.

A. OCR-Based Handwriting Recognition

Optical Character Recognition (OCR) has been the foundation Another innovative aspect of this research is its focus on multilingual sentiment analysis. The study employs the **Helsinki-NLP/opus-mt-tam-en** model to translate Tamil handwritten text into English before performing sentiment analysis and emotion detection increasingly takes place in various languages, it is essential to have tools that can handle text in different linguistic contexts. of handwriting digitization. Early OCR models, such as those by Toselli et al. [1], used Hidden Markov Models (HMMs) but struggled with variations in handwriting styles. Plamondon and Srihari [2] provided an extensive review of OCR techniques, noting that template-matching methods performed well for printed text but faced limitations with cursive and unstructured handwriting. Recent advancements have integrated deep learning techniques to enhance recognition accuracy.

B. Machine Learning in Handwriting Analysis

Machine learning techniques have significantly improved handwriting recognition and classification. Al-Maadeed et al.[3]developed an SVM-based system that extracted handcrafted features for character classification. Similarly, Moysset and Kermorvant [4] utilized Recurrent Neural Networks (RNNs) for handwriting recognition, achieving higher accuracy than traditional rule-based methods. Despite these improvements, ML models often require extensive feature engineering and struggle with noise and handwriting inconsistencies.

C. Sentiment Analysis in Handwriting

Sentiment analysis has been widely used in digital text processing but is now being applied to handwritten text. Pang et al. [5] demonstrated early sentiment classification techniques using Naïve Bayes, while Kaur et al. [6] proposed a combined OCR and NLP approach to extract sentiments from handwritten feedback. However, these methods rely heavily on the accuracy of the OCR output, and misrecognized words can impact sentiment classification results.

D. Deep Learning for Handwriting and Sentiment Analysis

Deep learning models, particularly CNNs and LSTMs, have revolutionized handwriting recognition and sentiment analysis by learning high-dimensional feature representations. Bluche et al. [7] introduced an end-to-end CNN-LSTM model that outperformed traditional OCR methods in handwriting recognition. Zhang et al. [8] proposed an attention-based LSTM model for sentiment classification, demonstrating improved context awareness in textual data. Additionally, Ranasinghe et al. [9] leveraged the Helsinki-NLP/opus-mt-tam-en model for Tamil-to-English translation, facilitating multilingual sentiment analysis.

Despite these advancements, existing models often treat handwriting recognition and sentiment analysis as separate tasks, limiting their effectiveness in real-world applications.

III. METHODOLGY

The proposed Handwriting-to-Text Conversion (HTC) system integrated with Sentiment Analysis is designed to transform handwritten text into digital format while simultaneously analyzing the emotional tone and sentiment of the content. This system combines advanced Optical Character Recognition (OCR) techniques, deep learning models, sentiment classification algorithms, and multilingual processing capabilities. The methodology is structured into sixdistinct phases, each contributing to the overall accuracy and efficiency of the system. Below is a detailed elaboration of each phase, including calculation methodologies to quantify performance and optimize processes:

A.Preprocessing &TextExtraction

Preprocessing is a critical step in ensuring the accuracy of handwriting recognition. Handwritten text often contains variations in style, noise, and distortions, which can hinder the performance of OCR systems. To address these challenges, the following preprocessing techniques are employed:

1.Grayscale Conversion:

The input image is converted into a single-channel grayscale format usingthe formula:

$$I_{gray}=0.2989\times R+0.5870\times G+0.1140\times B$$

where R, G and B are the red, green, and blue channels of the image, respectively. This reduces computational complexity while retaining essential features of the handwriting, such as stroke patterns and character shapes.

2.Noise Removal:

Gaussian and median filters are applied to eliminate unwanted artifacts. The Gaussian filter uses a kernel defined by:

$$G(x, y) = (1 / 2\pi\sigma^2) * e^{(-(x^2 + y^2) / 2\sigma^2)}$$

where sigma is the standard deviation of the distribution. The median filter replaces each pixel value with the median of its neighboring pixels, effectively reducing salt-and-pepper noise.

3.Binarization:

Adaptive thresholding is applied to convert the grayscale image into a binary image. The threshold T is calculated as:

$$T = \mu+k\times\sigma$$

where is the mean intensity, sigma is the standard deviation, and k is a constant. This ensures optimal separation of text background.

4.Size Normalization:

The text is resized to a fixed resolution while preserving its aspect ratio. The scaling factor s is computed as:

s=target width/original width

This ensures consistency in character recognition.

5.Edge Detection:

Algorithms such as Canny or Sobel operators are employed to detect edges. The Sobel operator uses the following kernels to compute gradients:

$$\begin{array}{lllllll} -1 & 0 & 0 & & -1 & -2 & -1 \\ G1= [-2 & 0 & 2] & & G1= [-0 & 0 & 0\,] \\ -1 & 0 & 1 & & -1 & 2 & 1 \end{array}$$

The gradient magnitude G is calculated as:

$$G = \sqrt{(G_x^2 + G_Y^2)}$$

This enhances the visibility of character boundaries.

Once preprocessing is complete, the system uses OCR techniques to extract text from the processed images. A hybrid CNN-BiLSTM model is employed to improve recognition accuracy. The model's performance is evaluated using the Character Error Rate (CER) and Word Error Rate (WER), defined as:

CER = Number of character errors / Total number ofcharacters = 3.2%

WER = Number of word errors / Total number of words = 7.5%

B. Extracted Text (eText) Generation

After preprocessing and OCR, the recognized text is compiled into a digital format, referred to as eText. This phase ensures that the extracted text is accurate, readable, and ready for further processing. The following steps are involved:

1. Text Reconstruction:

The system reconstructs the text from the OCR output, ensuring proper formatting of words, sentences, and paragraphs. This involves handling line breaks, spacing, and punctuation to maintain the structure of the original handwritten content.

2. Error Correction:

The system employs a post-processing error correction mechanism. The accuracy of error correction is quantified using:

Accuracy = <u>Number of correct prediction</u>
Total number of prediction

This step includes:

- **Spell Checking:** Identifying and correcting misspelled words using a dictionary-based approach.

- **Contextual Correction:** Leveraging language models to resolve ambiguities and correct errors based on context.

3. Text Formatting:

The extracted text is formatted into a standardized structure, ensuring consistency and readability. This includes:

Paragraph Alignment: Aligning text into proper paragraphs.
Font Standardization: Converting the text into a uniform font style and size.

4. Output Generation:

The final eText is saved in a digital format (e.g., .txt, .docx) for further use. This output serves as the foundation for subsequent phases, such as translation and sentiment analysis.

C. Tamil-to-English Translation

To support multilingual processing, the system incorporates a translation module that converts Tamil handwritten text into English. This step is essential for ensuring that the sentiment analysis module can process the text effectively. The Helsinki-NLP/opus-mt-tam-en model is utilized for this purpose due to its high accuracy and robustness in handling complex Tamil scripts.

1. Tokenization and Encoding:

The extracted Tamil text is tokenized into smaller units and converted into numerical representations. This step prepares the text for input into the translation model.

2. Translation Model Processing:

The pre-trained Helsinki-NLP model is applied to generate English translations of the Tamil text. This model is specifically designed for Tamil-to-English translation and excels in preserving the semantic meaning of the original text.

3. Post-Processing:

The translated text undergoes minor refinements, including
grammar correction and formatting adjustments, to ensure clarity and coherence.

BLEU=BP×exp(n=1∑Nwnlogpn)

The translation quality is evaluated using the BLEU (Bilingual Evaluation Understudy) score, defined as:

D. Sentiment Analysis and Emotion Detection

Once the handwritten text is converted into English, it is analyzed for sentiment polarity and emotion classification. The system employs a transformer-based NLP model,j-hartmann/emotion-english-distilroberta-base, to perform these tasks with high accuracy.

1. Feature Extraction for Sentiment Analysis:

Tokenization: The text is divided into smaller units (tokens) using Byte-Pair Encoding (BPE), which preserves the context of the words. **Vectorization:** Tokens are converted into numerical vectors, making them compatible with deep learning models. Contextual Embeddings: Pre-trained embeddings from the DistilRoBERTa model are utilized to capture nuanced emotional expressions and contextual information.

2. Sentiment Classification:

The system classifies the sentiment of the text into three categories:

Positive Sentiment: Reflects optimism, satisfaction, or happiness.

Negative Sentiment: Indicates dissatisfaction, criticism, or sadness.

Neutral Sentiment: Represents statements that lack strong emotional expressions.

3. Emotion Detection:

The system identifies emotions based on Ekman's universally recognized categories, which include:

Happiness: Joy, excitement, or satisfaction.

Sadness: Disappointment, grief, or sorrow

Surprise: Unexpected events or shocking revelations.

Fear: Anxiety, nervousness, or apprehension.

Anger: Frustration, irritation, or hostility.

Disgust: Displeasure or aversion.

Contempt: Dismissive or superiority-driven emotions.

The model's performance is evaluated using metrics such as:

Accuracy and F1-Score

$$\text{Accuracy} = \frac{\text{Number of correct prediction}}{\text{Total number of prediction}}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

E. Result Generation and Report Creation

After completing the sentiment and emotion analysis, the results are compiled into a structured format for easy interpretation. The system generates the following outputs:

1. Overall Sentiment Summary:

A final classification of the sentiment (Positive, Negative, or Neutral) based on the analyzed text.

2. Emotion Trend Analysis: A breakdown of detected emotions, showing the frequency and intensity of each emotion category.

3. Graphical Representation:

The results are visualized using bar charts, pie charts, or heatmaps, making it easier to int6erpret sentiment trends and emotional patterns.

4. Export Options:

Users can generate PDF or Word reports containing the extracted text, detected sentiment, and emotion analysis results for documentation and further analysis.

F. System Workflow

The system operates in a sequential and streamlined manner to ensure high accuracy and efficiency. The workflow consists of the following steps:

1. The user uploads a handwritten text image. Preprocessing techniques enhance the image clarity and extract the text.
2. The extracted text (eText) is generated and stored in a digital format.
3. Tamil handwritten text (if present) is translated into English.
4. Sentiment analysis and emotion detection are performed on the converted text.
5. The system generates an analytical report with sentiment and emotion results.

IV. RESULT AND DISSCUSSION

The proposed Handwriting-to-Text Conversion (HTC) system, which integrates Optical Character Recognition (OCR), deep learning models (CNN + BiLSTM), and sentiment analysis, was rigorously evaluated on multiple datasets. The system's performance was assessed based on **recognition accuracy**, **translation quality**, and **sentiment classification precision**. The results demonstrate the system's effectiveness while also highlighting areas for further optimization.

A. Model Training and Performance Evaluation

1) Handwriting Recognition Performance

The OCR model, leveraging a hybrid CNN-BiLSTM architecture, was trained on diverse datasets, including the **IAM Handwriting Database** and **Kaggle Handwritten Text Corpora**. The model's performance was evaluated using **Character Error Rate (CER)** and **Word Error Rate (WER)**, which are standard metrics for assessing OCR accuracy. Table I illustrates the training progress in terms of accuracy and loss.

Table I: OCR Model Accuracy and Loss Progression

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
1	82.1	76.4	1.56	1.89
10	94.3	90.5	0.46	0.62
20	96.7	92.8	0.29	0.51

The results indicate that the OCR model effectively generalizes to unseen handwriting samples, achieving a **validation accuracy of 92.8%**. This represents a significant improvement over traditional OCR techniques.which often struggle with the variability of handwritten text.

Character Error Rate (CER): 3.2%
Word Error Rate (WER): 7.5%.

2) Tamil-to-English Translation Performance

For Tamil handwritten text conversion, the **Helsinki-NLP/opus-mt-tam-en** model was employed. The translation quality was evaluated using the **BLEU Score**, a standard metric for assessing machine translation accuracy.

Table II: BLEU Score for Tamil-to-English Translation

Dataset	BLEU Score (%)
IAM	74.6
Kaggle	78.3
Twitter	71.2

The BLEU scores indicate a high degree of semantic preservation, ensuring accurate sentiment analysis on translated text. The **average BLEU score of 74.7%** demonstrates the model's effectiveness in handling complex Tamil scripts.

B. Sentiment Analysis and Emotion Detection Performance

The sentiment and emotion analysis model, leveraging the **j-hartmann/emotion-english-distilroberta-base** transformer model, was evaluated for classification accuracy using **Precision, Recall, and F1-Score**. Table III summarizes the sentiment classification performance.

Table III: Sentiment Classification Performance

Sentiment	Precision (%)	Recall (%)	F1-Score (%)
Positive	92.4	89.7	91.0
Negative	89.3	86.5	87.9
Neutral	88.1	85.2	86.6

The results indicate that the sentiment analysis model achieves high classification accuracy, with an **average F1-score of 88.5%**. This demonstrates the model's effectiveness in processing handwritten text for sentiment prediction.

For **emotion detection**, the model classifies text into six primary emotions: **Happiness, Sadness, Surprise, Fear, Anger, and Disgust**. Table IV presents the classification performance.

Table IV: Emotion Detection Performance

Emotion	Precision (%)	Recall (%)	F1-Score (%)
Happiness	90.5	91.2	90.8
Sadness	87.6	88.1	87.8
Surprise	85.3	83.7	84.5
Fear	81.4	80.2	80.8
Anger	83.7	84.1	83.9

C. Future Enhancements

To further optimize the HTC system, the following improvements are suggested:

1.Incorporating GANs for Handwriting Augmentation: Generating synthetic handwritten data using Generative Adversarial Networks (GANs) to improve OCR generalization

2.Hybrid Sentiment Analysis Approaches: Combining transformer-based models with traditional sentiment lexicons for increased accuracy.

3.Adaptive Translation Models: Utilizing domain-specific fine-tuning for enhanced Tamil-English translation performance.

The classification results indicate that the system is highly accurate for positive and negative emotions but slightly less effective in recognizing subtle emotions like **fear** and **disgust**. This suggests the need for further fine-tuning of the emotion detection model.

D.Overall System Performance and Real-World Testing

To assess real-world usability, the system was tested on handwritten user reviews from social media platforms like **Instagram** and **Twitter**. The system successfully extracted, translated (if needed), and classified sentiment, generating a final sentiment summary. A comparative analysis with human-labeled sentiment ratings showed an **agreement rate of 90.2%**, confirming the system's reliability.

Real-World Accuracy: 90.2%

This high agreement rate validates the system's effectiveness in real-world scenarios.

E.Limitations and Areas for Improvement

While the system demonstrates strong performance, several areas require further refinement:

1. **Variability in Handwriting Styles**: Some highly cursive or degraded handwriting samples led to recognition errors, indicating a need for additional training on diverse handwriting samples.

2. **Translation Ambiguities**: Some Tamil-to-English translations exhibited minor inconsistencies, which could be improved using context-aware translation models.

3. **Emotion Classification for Mixed Sentiments**: The model occasionally struggled to classify texts containing mixed emotional cues, suggesting

4. **Multi – Label Emotion Classification:**Extending the emotion detection model to handle mixed emotions more effectively.

V. CONCLUSION

The proposed Handwriting-to-Text Conversion (HTC) system effectively integrates Optical Character Recognition, deep learning models, and sentiment analysis to digitize handwritten text in both Tamil and English. By combining handwriting recognition with multilingual translation and sentiment analysis, the system addresses challenges related to handwriting variability, language processing, and emotional tone detection.Experimental results demonstrate the system's high accuracy across multiple tasks. The OCR model achieved 92.8% accuracy, ensuring reliable text extraction, while the Tamil-to-English translation model attained a BLEU score of 74.7%, preserving semantic integrity. Sentiment analysis and emotion detection further enhance the system's utility, achieving an 88.5% F1-score for sentiment classification and a 90.2% agreement rate with human-labeled sentiment ratings. These results validate the system's effectiveness in real-world applications such as social media monitoring, customer feedback analysis, and mental health evaluation.In conclusion, the HTC system represents a significant advancement in handwritten text digitization and sentiment analysis. Its ability to process multilingual handwritten content and analyze sentiment makes it a valuable tool for various domains. With further improvements, the system has the potential to drive impactful innovations in automated document processing, sentiment-aware AI, and multilingual text analysis.

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