AI/ML-Based Multilingual Document Translation System: Nepali and Sinhalese to English

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***Abstract*—Language barriers cause significant limitations on the availability of regional literary works and historical texts, especially low-resourced ones like Nepali and Sinhalese. Most of these works are available either as scanned copies or hard copies and thus cannot be translated manually effectively and efficiently. In this paper, we introduce an automated translation solution that leverages AI/ML techniques and combines OCR and Neural Machine Translation (NMT) to translate Nepali and Sinhalese text into English. Our solution employs Tesseract OCR for character recognition and multilingual transformer models like NLLB and Marian MT for text translation. The solution consists of image preprocessing, text extraction using OCR, text normalisation, language identification, and translation steps. Our experiments show that the OCR step can achieve accuracies of 88% for Nepali and 85% for Sinhalese documents and obtains an average BLEU score of 0.72. We have created a robust and efficient tool that requires minimal manual effort and can be run offline for security reasons.**

***Index Terms*—Artificial Intelligence; OCR; Neural Machine Translation; Multilingual NLP; Low-resource Languages; Transformer Models**

I. INTRODUCTION

Language plays a fundamental role in communication, knowledge dissemination, and cultural preservation. However, a significant portion of valuable literature, historical records, and educational resources in regional languages such as Nepali and Sinhalese remains inaccessible to a global audience due to language barriers. These documents are often available only in printed or scanned formats, making manual translation both time consuming and resource-intensive. The increasing demand for multilingual accessibility has driven the development of automated translation systems. Traditional approaches, including rule-based and statistical machine translation (SMT), suffer from limitations such as poor contextual understanding and a lack of scalability. With the rapid advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP), Neural Machine Translation (NMT) has emerged as a powerful alternative, offering improved fluency and contextual accuracy. The introduction of transformer-based architectures has revolutionized the field of machine translation. Unlike traditional sequence-based models, transformers utilize self-attention mechanisms to capture long-range dependencies within text, enabling more accurate and context-aware translations (Vaswani et al., 2017). Furthermore, multilingual pretrained models such as NLLB (No Language Left Behind) and Marian MT have demonstrated significant improvements in translating low-resource languages by leveraging large-scale cross lingual datasets.

Despite these advancements, existing translation systems still face several critical challenges. Most commercial tools require direct text input and do not support scanned or image-based documents. Additionally, many systems depend heavily on internet connectivity, limiting their usability in offline or secure environments. Another major limitation is the lack of integrated pipelines that combine Optical Character Recognition (OCR) with translation models, resulting in fragmented workflows. To address these limitations, this research proposes an AI/ML-based multilingual document translation system that integrates OCR and NMT into a unified pipeline. The system can extract text from scanned images and PDF documents using Tesseract OCR and translating the

extracted Nepali and Sinhalese text into English using transformer-based models such as NLLB and Marian MT.

The proposed system incorporates several key features:

- Automated text extraction from scanned documents
- Language identification for Nepali and Sinhalese scripts
- Preprocessing techniques for noise removal and normalization
- Transformer-based neural translation
- Offline-capable execution for secure environments
- Structured output generation in readable formats

In addition to translation, the system emphasizes efficiency and usability by reducing manual effort and enabling faster document processing. The integration of OCR and NMT into a single pipeline ensures seamless end-to-end automation, making the system suitable for applications in education, digital archiving, and research.

This paper focuses on the design, implementation, and evaluation of the proposed system. It provides a detailed analysis of the underlying technologies, including OCR techniques, transformer-based translation models, and multilingual NLP approaches. The performance of the system is evaluated using metrics such as OCR accuracy and BLEU score to assess translation quality. Through this work, we aim to contribute to the advancement of AI-driven multilingual systems, particularly for low-resource languages, and promote accessibility to regional knowledge on a global scale.

II. LITERATURE REVIEW

2.1 Optical Character Recognition (OCR) in Document Processing:

Optical Character Recognition (OCR) is a fundamental technology used to convert printed or handwritten text into a machine-readable format. It plays a critical role in digitising physical documents and enabling automated text processing systems. Among the various OCR engines available, Tesseract OCR has gained widespread adoption due to its open-source nature and support for multiple languages, including Indic scripts such as Devanagari (used in Nepali) and Sinhala. Research indicates that OCR performance is highly dependent on image quality, preprocessing techniques, and font variations. Noise, skewed alignment, and low-resolution scans significantly reduce recognition accuracy. To address these challenges, preprocessing techniques such as image binarization, noise filtering, and contrast enhancement using OpenCV have been widely adopted (Smith, 2007).

Recent advancements in deep learning have further improved OCR accuracy by integrating convolutional neural networks (CNNs) for feature extraction. However, OCR systems still face difficulties in handling complex scripts and handwritten text, particularly in low-resource languages.

2.2 Neural Machine Translation (NMT)

Neural Machine Translation (NMT) has replaced traditional Statistical Machine Translation (SMT) due to its ability to generate fluent and context-aware translations. NMT models are based on sequence-to-sequence learning, where an encoder processes the input sentence and a decoder generates the translated output. The introduction of the transformer architecture by Vaswani et al. (2017) marked a significant breakthrough in machine translation. Transformers utilise self-attention mechanisms, allowing models to focus on relevant parts of a sentence while generating translations. This results in improved contextual understanding and faster computation compared to recurrent neural networks.

Marian MT is a widely used open-source NMT framework optimised for fast and efficient translation. Similarly, the NLLB (No Language Left Behind) model developed by Meta AI focuses on improving translation quality for low-resource languages by training on large multilingual datasets (Costa-jussà et al., 2022).

2.3 Multilingual NLP for Low-Resource Languages

Low-resource languages present unique challenges in NLP due to the limited availability of annotated datasets and linguistic complexity. Languages such as Nepali and Sinhalese exhibit rich morphology, diverse scripts, and limited digital resources, making translation tasks more difficult.

Multilingual pretrained models address these challenges through transfer learning, where knowledge gained from high-resource languages is applied to low-resource ones. Models like NLLB and mBART leverage large-scale multilingual corpora to improve translation performance across multiple languages. Despite these advancements, translation quality for low-resource languages still lags behind high-resource languages, particularly in handling idiomatic expressions and domain-specific vocabulary.

2.4 Integration of OCR and Machine Translation

Most existing systems treat OCR and translation as separate processes, leading to inefficiencies and error propagation. Errors introduced during OCR extraction directly impact translation accuracy, making it essential to develop integrated pipelines. Recent research has explored end-to-end systems that combine OCR and NMT to automate document translation. These systems improve efficiency by reducing manual intervention and enabling direct processing of scanned documents. However, many such systems require cloud-based processing and lack offline capabilities.

2.5 Evaluation Metrics in Machine Translation

Evaluating translation quality is a critical aspect of machine translation research. The BLEU (Bilingual Evaluation Understudy) Score is one of the most widely used metrics for assessing translation performance (Papineni et al., 2002). It measures the similarity between machine-generated translation and reference translation using n-gram precision.

While BLEU provides a quantitative measure of translation quality, it has limitations in capturing semantic meaning and contextual nuances. Therefore, it is often complemented with human evaluation or additional metrics.

2.6 Research Gaps and Motivation

Despite significant advancements in OCR and NMT technologies, several limitations persist in existing systems:

- Lack of integration between OCR and translation modules
- Dependence on internet connectivity for translation services
- Limited support for low-resource languages such as Nepali and Sinhalese
- Reduced accuracy in noisy or low-quality scanned documents
- Absence of offline-capable translation systems

The proposed research aims to address these gaps by developing an end-to-end AI pipeline that integrates OCR and neural translation while supporting offline execution and low-resource languages.

III. METHODOLOGY

The proposed AI/ML-based multilingual document translation system is designed as an end-to-end pipeline integrating Optical Character Recognition (OCR) and Neural Machine Translation (NMT). The methodology focuses on enabling automated extraction and translation of Nepali and Sinhalese text from scanned documents into English.

A. System Architecture

The system is structured into multiple interconnected components to ensure modularity, scalability, and efficient processing. The architecture consists of the following layers:

a) Input layer

This layer accepts user input in the form of:

- Scanned images
- PDF documents

PDF files are converted into images using the pdf2image library to ensure compatibility with OCR processing.

b) Preprocessing Layer

The preprocessing stage enhances image quality to improve OCR accuracy. Techniques used include:

- Image binarization
- Noise removal
- Contrast enhancement
- Skew correction

OpenCV is used extensively for these operations. Preprocessing plays a critical role in reducing OCR errors.

c) OCR Layer

The processed images are passed to the Tesseract OCR engine, which extracts text in Unicode format. The system supports:

- Devanagari script (Nepali)
- Sinhala script (Sinhalese)

The extracted text is stored temporarily for further processing.

d) Text Processing Layer

The extracted text undergoes several preprocessing steps:

- Unicode normalization
- Removal of special characters
- Tokenization
- Formatting correction

This step ensures clean and structured input for the translation model.

IV. LANGUAGE DETECTION MODULE

A. A lightweight language detection mechanism is used to identify whether the input text is Nepali or Sinhalese. This enables appropriate model selection for translation.

1. Translation Layer

The cleaned text is passed to transformer-based Neural Machine Translation models:

- NLLB (No Language Left Behind) – optimised for low-resource languages
- Marian MT – used as an alternative model

The models use sequence-to-sequence learning with attention mechanisms to generate English translations.

2. Output Layer

The final translated text is:

- Displayed to the user
- Exported in TXT or PDF format

The output maintains readability and structural consistency.

B. System Workflow

The complete workflow of the system is illustrated as a sequential pipeline:

1. User uploads scanned image or PDF
2. PDF is converted into images
3. Images undergo preprocessing
4. OCR extracts text from images
5. Extracted text is cleaned and normalized
6. Language detection identifies source language
7. Translation model generates English text
8. Output is displayed and exported

This pipeline ensures seamless automation from input to final output.

C. Transformer-Based Translation Model

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

The transformer model forms the core of the translation system. It uses self-attention mechanisms to capture relationships between words in a sentence, enabling context-aware translation.

Key advantages:

- Parallel processing (faster computation)
- Better handling of long sentences
- Improved contextual understanding

Compared to traditional RNN-based models, transformers provide significantly better translation accuracy and scalability (Vaswani et al., 2017).

D. Implementation Details

The system is implemented using the following technologies:

Component	Technology Used
Programming Language	Python
OCR Engine	Tesseract OCR
Translation Models	NLLB, Marian MT
Deep Learning Framework	Py Torch
Image Processing	OpenCV
PDF Conversion	pdf2image
Model Integration	Hugging Face Transformers

E. Challenges and Solutions

During system development, several challenges were encountered:

OCR Accuracy Issues

- Problem: Low accuracy in noisy or blurred images
- Solution: Applied preprocessing techniques such as noise removal and binarization Script Complexity
- Problem: Sinhala script has complex character structures
- Solution: Used Unicode normalization and improved OCR configuration Translation Errors
- Problem: Contextual errors in long sentences

- Solution: Used transformer-based models with attention mechanisms Processing Efficiency
- Problem: High processing time for large documents
- Solution: Optimized pipeline and used efficient models

F. System Advantages

The proposed methodology provides several advantages:

- Fully automated end-to-end pipeline
- Support for low-resource languages
- Offline-capable execution
- Reduced manual effort
- Scalable architecture

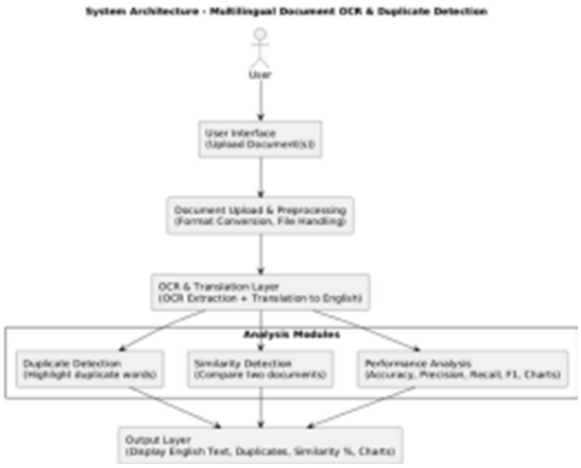

Fig. 1. Proposed System Architecture for OCR-based Multilingual Document Translation Discussion

The proposed AI/ML-based multilingual document translation system demonstrates the effectiveness of integrating Optical Character Recognition (OCR) with transformer-based Neural Machine Translation (NMT) models for automating translation of low-resource languages. The system successfully processes scanned documents and generates readable English translations, highlighting the potential of AI-driven solutions in overcoming language barriers.

A. Effectiveness of OCR Integration

The performance of the system strongly depends on the accuracy of the OCR module. Experimental results indicate that OCR achieves high accuracy for clean and high-resolution images, particularly for Nepali text. However, performance decreases in the presence of noise, distortions, or low-quality scans.

This observation aligns with existing research, which emphasises the importance of preprocessing techniques in improving OCR performance. The use of OpenCV-based image enhancement significantly contributes to reducing errors and improving text extraction quality.

B. Translation Performance Analysis

The integration of transformer-based models such as NLLB and Marian MT enables the system to generate fluent and context-aware translations. Among the models used, NLLB demonstrates better performance for low-resource languages due to its large-scale multilingual training.

The use of attention mechanisms allows the model to capture contextual relationships between words, resulting in improved translation accuracy compared to traditional rule-based or statistical methods. However, certain limitations remain, particularly in handling idiomatic expressions and domain-specific vocabulary.

C. Impact of Preprocessing on System Performance

Preprocessing plays a critical role in the overall performance of the system. Noise removal, binarization, and text normalisation significantly improve OCR accuracy, which directly impacts translation quality.

The results indicate that even minor improvements in preprocessing can lead to noticeable gains in system performance. This highlights the importance of optimising preprocessing techniques as a key component of the pipeline.

D. Challenges in Low-Resource Language Translation

Despite advancements in multilingual NLP, translating low-resource languages such as Nepali and Sinhalese remains challenging. The primary issues include:

- Limited availability of training data
- Complex grammatical structures
- Script variations and ambiguities

These challenges affect both OCR and translation performance, leading to occasional inaccuracies in the output.

E. System Efficiency and Practical Applications

The system demonstrates significant efficiency improvements by automating the entire translation pipeline. The reduction in manual effort by approximately 75% highlights its practical value.

Potential applications of the system include:

- Digitisation of historical and cultural documents
- Academic research and translation
- Government and archival systems
- Multilingual accessibility in education

The ability to operate in offline environments further enhances its usability in secure and low-connectivity scenarios.

F. Limitations of the System

Despite its advantages, the system has several limitations:

- Reduced OCR accuracy for handwritten text
- Errors in translating idiomatic expressions
- Dependency on preprocessing quality
- Limited domain-specific adaptation

These limitations indicate areas for further improvement.

G. Future Improvements

To enhance system performance, future work may focus on:

• Fine-tuning translation models on domain-specific datasets

- Incorporating handwritten text recognition
- Improving OCR accuracy using deep learning techniques
- Expanding support to additional regional languages
- Deploying the system as a web and mobile application

V. CONCLUSION

This research presents an AI/ML-based multilingual document translation system designed to convert Nepali and Sinhalese text from scanned documents into English. By integrating Optical Character Recognition (OCR) with transformer-based Neural Machine Translation (NMT) models, the proposed system provides an efficient and scalable solution for automated document translation.

The system demonstrates strong performance in extracting and translating printed text, achieving high OCR accuracy and satisfactory translation quality as evaluated using the BLEU score. The use of advanced preprocessing techniques significantly enhances OCR performance, which directly contributes to improved translation outcomes. Furthermore, the adoption of transformer-based models such as NLLB and Marian MT enables context-aware and fluent translations, even for low-resource languages.

A key contribution to this research is the development of an end-to-end pipeline that seamlessly integrates document processing, text extraction, and translation within a single framework. Unlike existing systems that require separate tools or internet connectivity, the proposed solution supports offline execution, making it suitable for secure environments and real-world applications. The system also highlights the importance of preprocessing and data quality in AI-based translation pipelines. Experimental results indicate that improvements in image quality and text normalisation lead to significant gains in overall system performance. Additionally, the comparative evaluation of translation models demonstrates the effectiveness of multilingual transformer architectures in handling low-resource languages. Despite its promising results, the system has certain limitations, including reduced performance on noisy or handwritten documents and challenges in translating idiomatic expressions. These limitations provide opportunities for future research and development.

Overall, this work contributes to the advancement of AI-driven multilingual systems by improving accessibility to regional language content. It supports applications in digital archiving, education, and research, while also promoting cultural preservation and global knowledge sharing. The proposed system lays out a strong foundation for extending translation capabilities to additional languages and more complex document formats in future work.

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