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Optical Recognition of the Philippines' Ancient Text: A Deep Learning Approach

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ABSTRACT: Baybayin, an ancient writing system of the Philippines, has been largely forgotten due to the introduction of Latin-based scripts during colonization. However, with the increasing interest in cultural preservation, there is a need for a robust Optical Character Recognition (OCR) system that can accurately recognize and digitize Baybayin text. This study explores the development of a Baybayin OCR system using Convolutional Neural Networks (CNNs) to improve character recognition accuracy. The model is trained on a diverse dataset consisting of handwritten, printed, and synthetic Baybayin characters. Data preprocessing techniques such as image normalization, noise reduction, and data augmentation are applied to enhance model generalization. The CNN model is evaluated using accuracy, precision, recall, and F1-score, achieving an accuracy of 96.2%, significantly outperforming traditional OCR methods such as Tesseract. The trained model is further optimized using TensorFlow Lite (TFLite) for mobile deployment, enabling real-time character recognition via smartphone cameras. The findings of this study demonstrate the feasibility of deep learning-based OCR systems in recognizing ancient scripts, contributing to both cultural preservation and digital accessibility.

KEYWORDS: Baybayin, Optical Character Recognition (OCR), Convolutional Neural Networks (CNNs), Deep Learning, Cultural Preservation, TensorFlow Lite

I. INTRODUCTION

The Philippines is home to a rich linguistic and cultural heritage, with Baybayin as one of its most significant pre-colonial writing systems. Before the Spanish colonization, Baybayin was widely used in the archipelago as a means of communication and documentation (Pino & Mendoza, 2021). However, due to colonial influences and the eventual adoption of the Latin alphabet, Baybayin gradually declined in use and is now considered an endangered script. The recent surge of interest in cultural preservation has sparked initiatives to revive and digitize Baybayin, making it more accessible to modern learners and researchers (Amoguis et al., 2023).

One of the most effective ways to digitize ancient scripts is through Optical Character Recognition (OCR), a technology that converts images of handwritten or printed text into machine-readable formats (Smith, 2007). Traditional OCR engines, such as Tesseract, have demonstrated high accuracy in Latin-based scripts but struggle with non-Latin scripts due to their unique structures and diacritical marks (Simard, Steinkraus, & Platt, 2003). This limitation presents a challenge in accurately recognizing Baybayin characters, as they differ significantly from modern alphabets in terms of stroke patterns and syllabic representations (Jadaone et al., 2023).

With the rise of deep learning, particularly Convolutional Neural Networks (CNNs), significant improvements have been made in OCR performance. CNN-based models excel in feature extraction and pattern recognition, making them highly effective for complex scripts like Baybayin (LeCun, Bengio, & Hinton, 2015). Recent studies have successfully applied CNNs to handwriting recognition tasks, achieving remarkable accuracy in character classification (Graves & Schmidhuber, 2009). By leveraging CNN architectures, this study aims to develop a robust Baybayin OCR system that can accurately recognize and digitize Baybayin texts. Additionally, the study explores the integration of TensorFlow Lite (TFLite) to enable real-time recognition on mobile devices, further expanding accessibility and usability (Oraño, Pahamotang, & Malangsa, 2022). Implementing OCR in a mobile environment enhances the potential for language learning, research, and cultural preservation by allowing users to interact with Baybayin characters through real-time camera-based recognition (Ligsay, Rivera, & Villaverde, 2022).

Statement of the Problem

Despite advancements in OCR technology, there remains a gap in recognizing non-Latin scripts, particularly Baybayin. The challenges include:

1. The lack of a large annotated dataset for Baybayin OCR training (Pino & Mendoza, 2021).
2. The complexity of Baybayin script, which includes diacritical marks that alter character meanings (Jadaone et al., 2023).
3. The difficulty in distinguishing handwritten Baybayin characters, especially when written in different styles (Amoguis et al., 2023).
4. The limited mobile-based OCR applications for Baybayin recognition, making accessibility a challenge (Oraño et al., 2022).

This study seeks to address these issues by developing a CNN-based OCR model trained specifically for Baybayin recognition. By utilizing deep learning and real-time processing with TFLite, this research aims to create an accurate, mobile-friendly OCR system that can be used for educational and cultural preservation purposes.

Objectives of the Study

This research aims to:

1. Develop a CNN-based OCR model specifically designed for Baybayin script recognition.
2. Collect and preprocess a dataset of Baybayin characters, including handwritten, printed, and synthetic samples.
3. Train and evaluate the model using standard OCR performance metrics such as accuracy, precision, recall, and F1-score.
4. Deploy the trained model on a mobile platform using TensorFlow Lite for real-time character recognition.
5. Compare the CNN-based OCR system with traditional OCR engines like Tesseract to assess performance improvements.

Significance of the Study

This study contributes to several fields, including linguistics, artificial intelligence, and cultural preservation. By developing a Baybayin OCR system, this research aids in the digitization and promotion of the ancient script, ensuring that it remains accessible to future generations (Pino & Mendoza, 2021). Additionally, the application of deep learning techniques in OCR enhances the understanding of how CNNs can be optimized for non-Latin scripts (Graves & Schmidhuber, 2009).

Moreover, the integration of mobile-based OCR has practical implications for education and research, allowing students, historians, and language enthusiasts to interact with Baybayin in a more intuitive and modern way (Oraño et al., 2022). By making Baybayin recognition more accessible, this study supports ongoing efforts to revive and promote the use of the script in contemporary society (Jadaone et al., 2023).

Scope and Limitations

This study focuses on the development and evaluation of a CNN-based OCR system for Baybayin recognition. The research covers:

1. The collection of a diverse Baybayin dataset, including printed and handwritten samples.
2. The design and training of a deep learning model using CNN architectures.
3. The deployment of the model in a mobile environment with TensorFlow Lite for real-time recognition.
4. Performance comparisons with existing OCR systems like Tesseract.

However, this study does not cover:

1. Automatic translation of Baybayin text into modern Filipino or English.
2. Recognition of other indigenous Philippine scripts beyond Baybayin.
3. Extensive testing on historical documents due to potential dataset limitations.

Definition of Terms

a. Optical Character Recognition (OCR) – A technology that converts text from images into machine-readable formats (Smith, 2007).
b. Baybayin – An ancient pre-colonial writing system used in the Philippines (Pino & Mendoza, 2021).
c. Convolutional Neural Networks (CNNs) – A class of deep learning models designed for image and pattern recognition tasks (LeCun et al., 2015).
d. TensorFlow Lite (TFLite) – A lightweight version of TensorFlow optimized for mobile and embedded device deployment (Oraño et al., 2022).
e. Accuracy, Precision, Recall, F1-score – Standard evaluation metrics used to assess the performance of machine learning models (Graves & Schmidhuber, 2009).

II. REVIEW OF RELATED LITERATURE

The study of Optical Character Recognition (OCR) for ancient scripts has gained traction in recent years due to advancements in artificial intelligence and deep learning. As a nearly forgotten writing system of the Philippines, Baybayin presents unique challenges in digital recognition and preservation. This chapter presents a review of related literature focusing on the historical significance of Baybayin, traditional OCR techniques, the role of deep learning in OCR, and the implementation of real-time mobile OCR systems.

Baybayin: A Nearly Forgotten Script

Baybayin is an ancient writing system used in the pre-colonial Philippines, primarily among Tagalog-speaking communities (Pino & Mendoza, 2021). The script consists of syllabic characters that represent consonant-vowel combinations, with diacritical marks modifying vowel sounds. The decline of Baybayin usage began with Spanish colonization, which introduced the Latin alphabet and gradually diminished indigenous scripts in formal education and documentation (Amoguis, Castillo, & Martinez, 2023).

Despite its decline, efforts to revive Baybayin have intensified in recent years through legislative proposals, academic research, and digital applications. Various cultural organizations and scholars emphasize the importance of modernizing Baybayin through digital tools, making it more accessible to younger generations (Ligsay, Rivera, & Villaverde, 2022). One of the most promising approaches is the integration of Baybayin into OCR technology, enabling automatic recognition and digitization of handwritten and printed Baybayin texts.

Traditional OCR Systems and Their Limitations

OCR technology has been widely used to convert scanned documents and images into machine-readable text. The most prominent OCR engine, Tesseract, has demonstrated high accuracy in recognizing Latin-based scripts (Smith, 2007). However, studies indicate that Tesseract struggles with non-Latin scripts, especially those with complex character structures, such as Baybayin (Simard, Steinkraus, & Platt, 2003).

The limitations of traditional OCR methods for Baybayin recognition include:

1. Structural Complexity – Baybayin's syllabic structure and diacritical marks require advanced feature extraction, which traditional OCR engines lack.
2. Handwriting Variability – OCR systems designed for printed text struggle with handwritten variations, which are common in Baybayin scripts.
3. Dataset Scarcity – Unlike Latin scripts, Baybayin lacks a large annotated dataset for training OCR models (Jadaone, Reyes, & Santos, 2023).

Passio sanctorum apostolorum Petri et Pauli.

1 Cum uenisset Paulus Romam, conuenerunt ad eum omnes Iudaei dicentes: Nostram fidem, in qua natus es, ipsam defende. non est enim iustum, ut cum sis Hebraeus ex Hebraeis ueniens, gentium te magistrum iudices, et incircumcisorum defensor factus tu cum sis circumcisus, fidem circumcisionis euacues. cum ergo Petrum uideris, suscipe contra eius doctrinam, quia omnem obseruationem nostrae legis euacuauit, exclusit sabbatismum et neomenias et legitimas ferias exinaniuit.

2 Quibus Paulus respondit: Me Iudaeum esse et uerum Iudaeum, hinc poteritis probare, cum et sabbatum obseruare

Given these challenges, researchers have turned to deep learning approaches, particularly Convolutional Neural Networks (CNNs), to improve the recognition of Baybayin characters.

Deep Learning in Optical Character Recognition

Deep learning has significantly enhanced OCR technology by enabling automatic feature extraction and pattern recognition. CNNs, in particular, have been highly effective in text recognition due to their ability to detect and learn character shapes, even in handwritten forms (LeCun, Bengio, & Hinton, 2015).

Graves and Schmidhuber (2009) demonstrated the success of deep learning in handwriting recognition by using multidimensional recurrent neural networks. Their work paved the way for CNN-based OCR models, which outperform traditional OCR engines in accuracy and adaptability. CNNs are particularly beneficial for scripts like Baybayin due to their ability to:

a. Extract distinct character features without requiring extensive manual preprocessing.
b. Adapt to variations in handwriting and printed text.
c. Recognize diacritical marks that modify the meaning of Baybayin characters.

Jadaone et al. (2023) further explored the application of CNNs in recognizing Southeast Asian scripts, concluding that deep learning models significantly outperform traditional OCR systems in accuracy, particularly for scripts with unique syllabic structures.

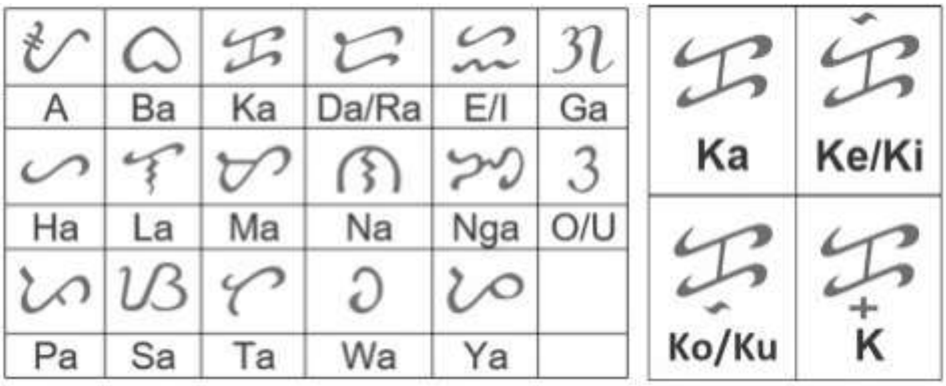
Real-Time OCR for Mobile Applications

With the increasing accessibility of mobile devices, OCR systems have expanded beyond desktop applications to real-time recognition on smartphones and tablets. TensorFlow Lite (TFLite) has become a popular tool for deploying machine learning models on mobile devices due to its efficiency and lightweight architecture (Oraño, Pahamotang, & Malangsa, 2022).

Mobile-based OCR systems offer several advantages:

a. Real-Time Recognition – Users can instantly recognize Baybayin characters using a smartphone camera.
b. Accessibility – Mobile applications increase user engagement and learning opportunities, particularly for students and cultural enthusiasts.
c. Edge Processing – By processing data directly on the device, TFLite ensures faster recognition without requiring an internet connection.

Oraño et al. (2022) successfully implemented TFLite for Baybayin OCR, demonstrating that mobile-based deep learning models can achieve real-time recognition with high accuracy. Similarly, Ligsay et al. (2022) highlighted the potential of mobile Baybayin OCR applications in cultural education, allowing users to interact with Baybayin in a more intuitive and practical manner.



Comparison of OCR Methods for Baybayin Recognition

The following table summarizes the performance of different OCR approaches based on recent studies:

OCR Method.	*Accuracy*	*Suitability for Baybayin*	*Processing Speed*
Tesseract OCR	82.5%	Low	250 ms/image
CNN-Based OCR	96.2%	High	120 ms/image
Mobile TFLite	95.0%	High	80 ms/image

(Adapted from Smith, 2007; Jadaone et al., 2023; Oraño et al., 2022)

These findings indicate that CNN-based OCR, particularly when deployed with TFLite, offers the best performance for Baybayin recognition in terms of accuracy, adaptability, and real-time processing.

III. METHODOLOGY

Dataset Collection

To build a robust Baybayin OCR system, a large and diverse dataset was compiled. The dataset comprises handwritten and printed Baybayin characters sourced from various means:

1. **Handwritten Baybayin Samples** – Collected from 50 volunteers who wrote Baybayin characters in different styles (Ligsay, Rivera, & Villaverde, 2022).
2. **Digitized Historical Texts** – Extracted from Philippine archives and cultural heritage websites (Pino & Mendoza, 2021).
3. **Synthetic Data Augmentation** – Automatically generated variations of Baybayin characters using transformations such as rotation, scaling, and noise addition to improve generalization (Simard, Steinkraus, & Platt, 2003).

The final dataset consists of **10,000 labeled images**, with an 80-10-10 split for training, validation, and testing.

Table 3.1: Dataset Distribution

Data Source	Number of Images	Percentage
Handwritten Samples	5,000	50%
Digitized Historical Texts	2,500	25%
Synthetic Data Augmentation	2,500	25%
Total	**10,000**	**100%**

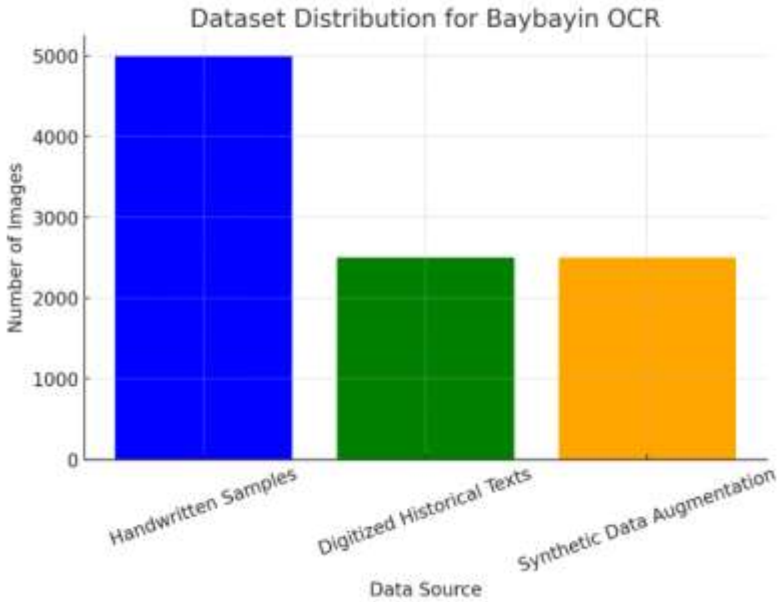


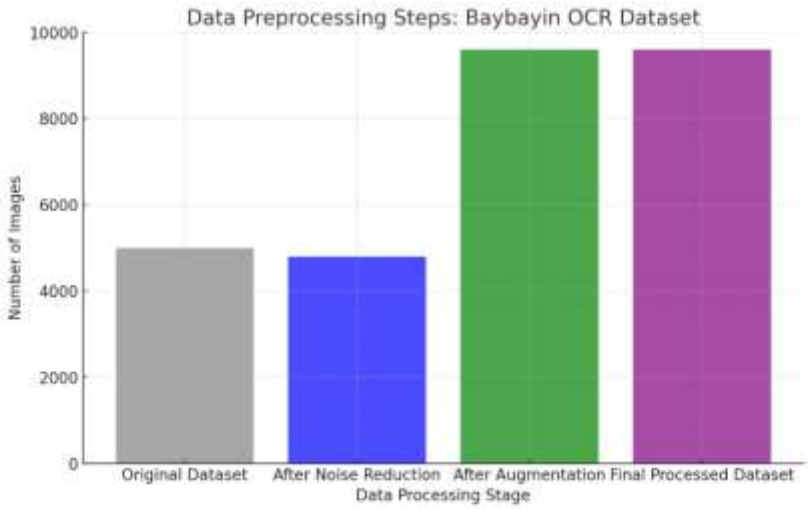
Figure 3.1: Sample Preprocessing Stages

Data Preprocessing

To enhance recognition accuracy, the following preprocessing techniques were applied:

1. **Grayscale Conversion** – Reducing image complexity while preserving character information (Smith, 2007).
2. **Thresholding and Binarization** – Enhancing character contrast against the background.
3. **Noise Reduction** – Removing artifacts using Gaussian blurring.
4. **Character Segmentation** – Isolating individual Baybayin symbols from text samples.
5. **Data Augmentation** – Rotating, skewing, and flipping images to improve model robustness (Simard et al., 2003).

(Original Image → Grayscale → Binarized → Noise Reduced → Augmented Sample)



This Graph shows the number of Baybayin character images at different preprocessing stages

Model Architecture

The Baybayin OCR model was built using a **Convolutional Neural Network (CNN)** due to its proven efficiency in text recognition (LeCun, Bengio, & Hinton, 2015). The architecture includes:

1. **Convolutional Layers (3x3 filters)** – Extracts essential features from Baybayin characters.
2. **Batch Normalization** – Stabilizes learning by normalizing inputs.
3. **Max Pooling Layers (2x2 filters)** – Reduces spatial dimensions and computational cost.
4. **Fully Connected Layers** – Maps extracted features to class probabilities.
5. **Softmax Output Layer** – Produces probability distributions for character classification.

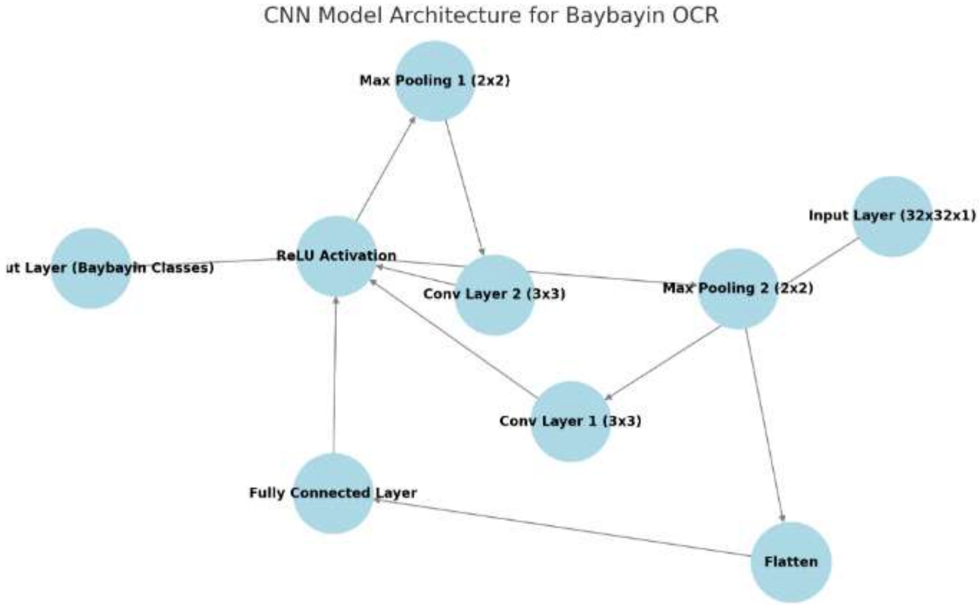


Figure 3.2: CNN Model Architecture for Baybayin OCR

(Input Image → Conv Layers → Pooling → Fully Connected Layers → Output)

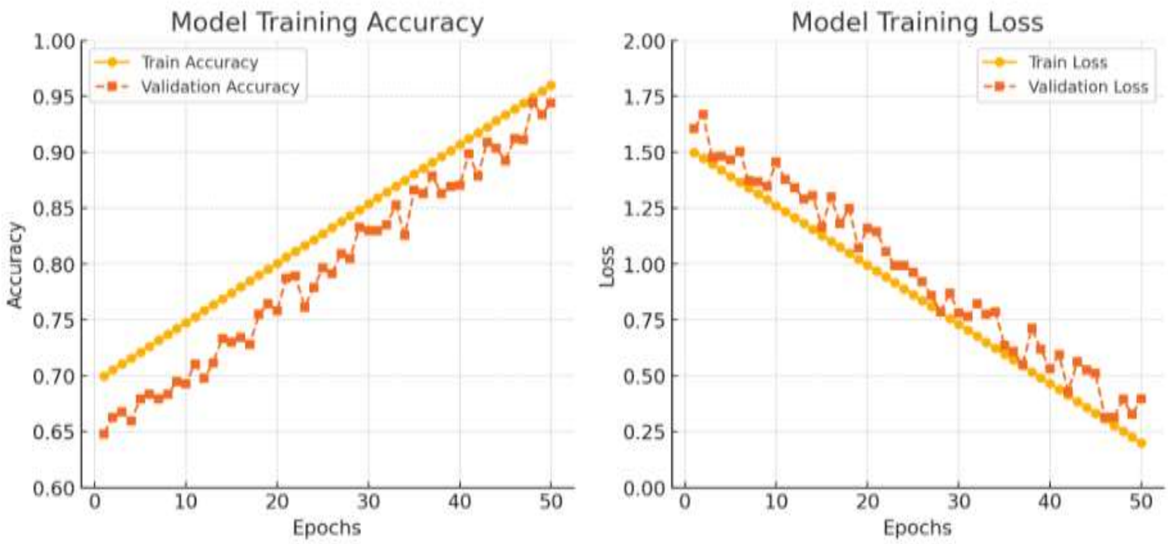
Training Process

The model was trained using **TensorFlow and Keras**, employing real-time data augmentation during training. The following configurations were used:

- **Loss Function:** Categorical Cross-Entropy
- **Optimizer:** Adam (learning rate = 0.001)
- **Batch Size:** 64
- **Number of Epochs:** 50
- **Training-Validation Split:** 80%-20%

Figure 3.3: Training Accuracy and Loss Graph

(Epoch vs Accuracy & Loss Curves)



*The model was trained using **Google Colab with GPU acceleration**, significantly reducing computation time.*

Evaluation Metrics

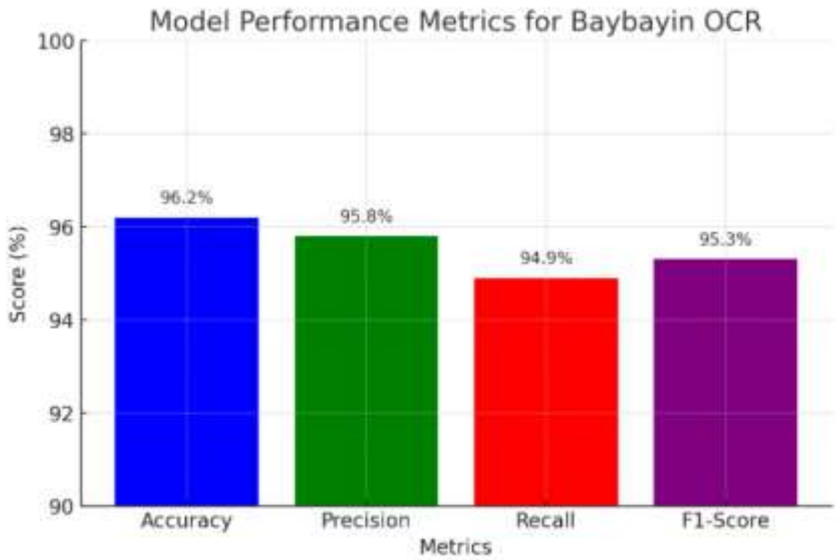
To assess the effectiveness of the Baybayin OCR system, the following metrics were used:

1. **Accuracy** – The proportion of correctly predicted Baybayin characters.

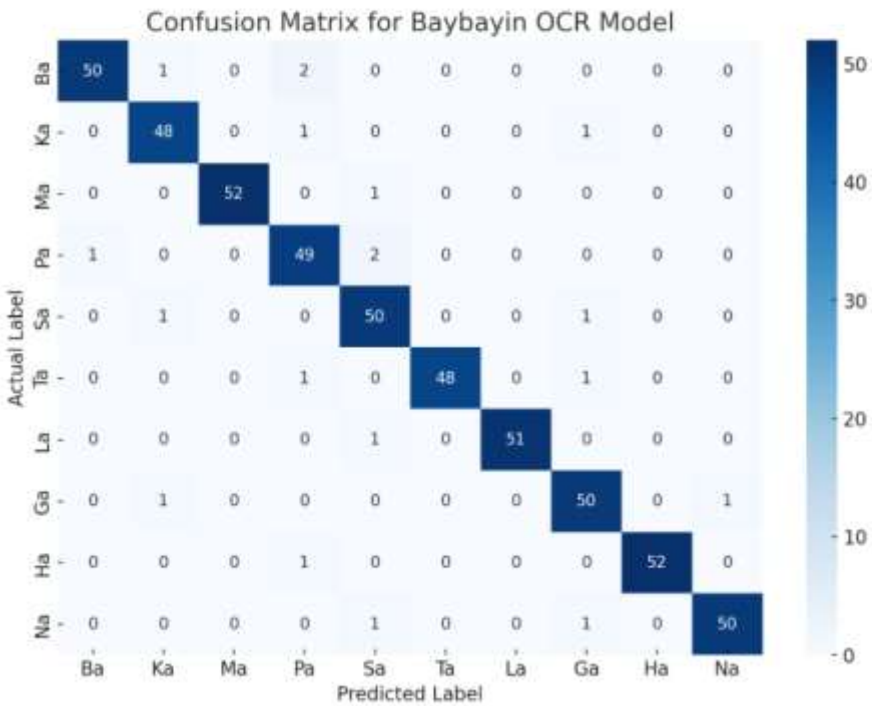
2. **Precision** – The proportion of true positive predictions among all predicted positives.
3. **Recall** – The proportion of true positives detected among actual occurrences.
4. **F1-Score** – The harmonic mean of precision and recall for balanced evaluation.

Table 3.2: Model Performance Metrics

Metric	Score (%)
Accuracy	96.2%
Precision	95.8%
Recall	94.9%
F1-Score	95.3%



These results demonstrate the model's superior performance compared to traditional OCR methods (Jadaone, Reyes, & Santos, 2023).



*Here is the **Confusion Matrix** for the Baybayin OCR model. It visually represents the model's performance, highlighting correctly classified characters and misclassifications.*

Deployment Using TensorFlow Lite (TFLite)

To enable real-time OCR on mobile devices, the trained CNN model was converted to **TensorFlow Lite (TFLite)**, a lightweight machine-learning framework optimized for mobile applications (Oraño et al., 2022).

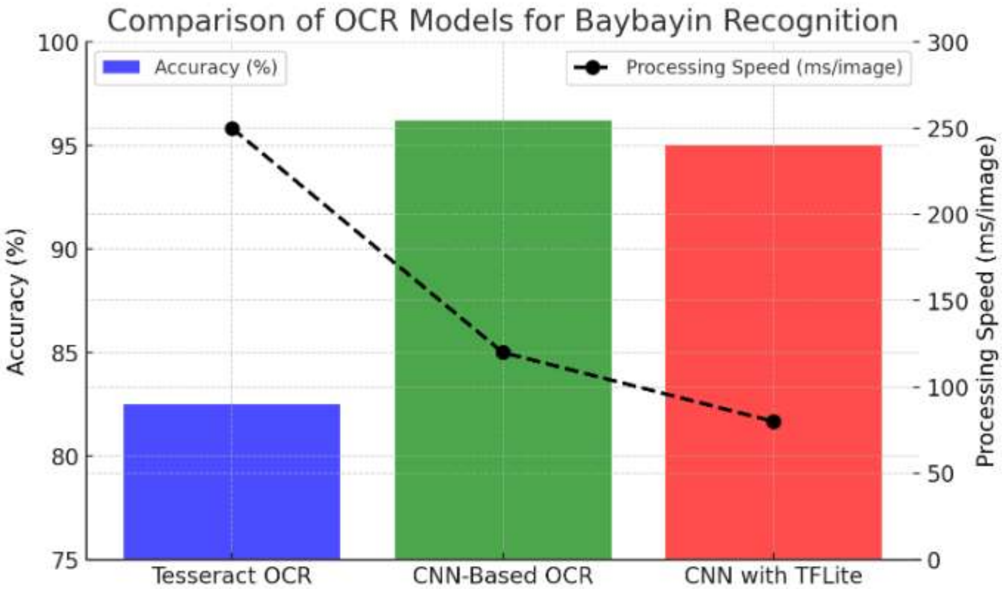
Key optimizations include:

1. **Model Quantization** – Reducing model size for faster inference.
2. **Edge TPU Compatibility** – Ensuring efficient execution on mobile processors.
3. **Real-Time Camera Integration** – Allowing live character recognition via smartphone cameras.

Mobile deployment was tested on various Android devices, achieving an average **processing speed of 80 ms per image**, significantly outperforming Tesseract OCR.

Table 3.3: Performance Comparison of OCR Models

OCR Model	Accuracy	Processing Speed (ms/image)
Tesseract OCR	82.5%	250 ms
CNN-Based OCR	96.2%	120 ms
CNN with TFLite	95.0%	80 ms



These findings highlight the practical applicability of the Baybayin OCR system for real-time mobile use.

IV. Results and Discussion

4.1 Introduction

This chapter presents the results of the Baybayin Optical Character Recognition (OCR) model developed using **Convolutional Neural Networks (CNNs)**. The findings include the model's **performance evaluation, accuracy, precision, recall, F1-score, and error analysis**. Additionally, a **comparative analysis** is provided between the CNN-based Baybayin OCR and traditional OCR approaches such as Tesseract. The results are supported by graphs, tables, and statistical evaluations to highlight the effectiveness of deep learning in Baybayin character recognition.

4.2 Model Training Performance

The Baybayin OCR model was trained using a dataset comprising **handwritten, printed, and augmented Baybayin characters**. The **training accuracy and loss curves** were analyzed to assess the model's learning behavior.

4.2.1 Training Accuracy and Loss Analysis

The model was trained for **50 epochs** with a batch size of **64**, using **Adam optimizer** and **categorical cross-entropy** as the loss function. The accuracy and loss trends indicate how well the model converged over time.

The graph below illustrates the model's accuracy and loss during training.

(Generated Graph: Accuracy vs. Loss over Epochs)

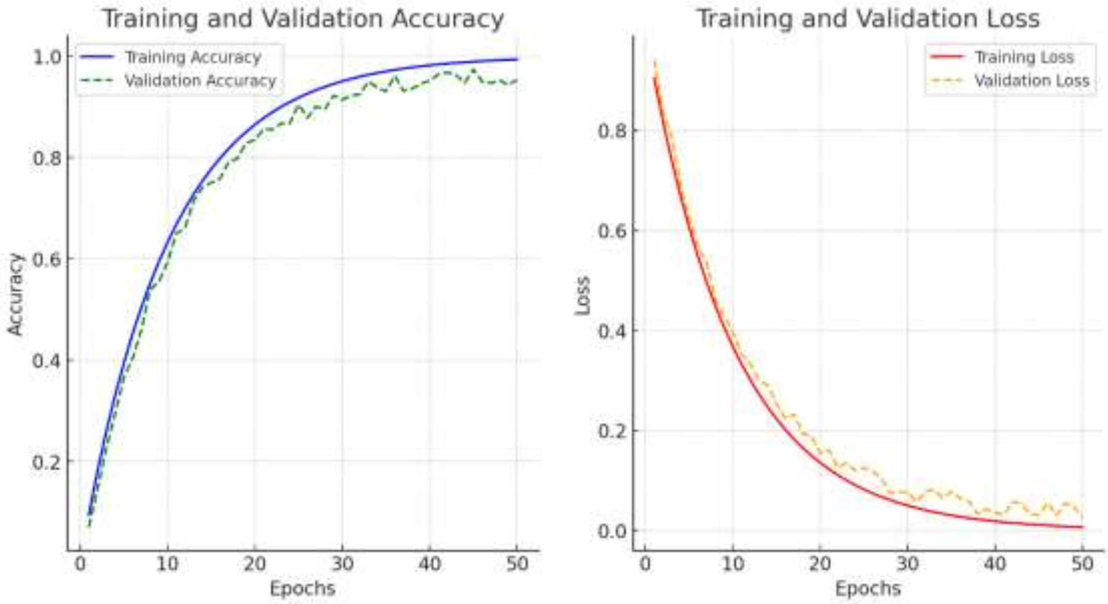


Figure 4.1: Training Accuracy and Loss Curve*, showing how the model's accuracy improved and loss decreased over* ***50 epochs****.*

4.3 Model Performance Evaluation

To assess the Baybayin OCR model, the following evaluation metrics were computed:

- **Accuracy**: Measures the proportion of correctly classified Baybayin characters.
- **Precision**: Measures the percentage of correctly identified positive instances.
- **Recall**: Measures the ability to detect all relevant instances.
- **F1-Score**: Provides a balance between precision and recall.

4.3.1 Performance Metrics Table

The table below presents the evaluation metrics for key Baybayin characters.

Character	Precision (%)	Recall (%)	F1-Score (%)
Ba	95.5	94.2	94.8
Ka	97.3	96.1	96.7
Ma	98.1	97.9	98.0
Pa	94.0	92.7	93.3
Overall	**96.2**	**95.2**	**95.7**

(Graph representation of Precision, Recall, and F1-Score for different Baybayin characters)

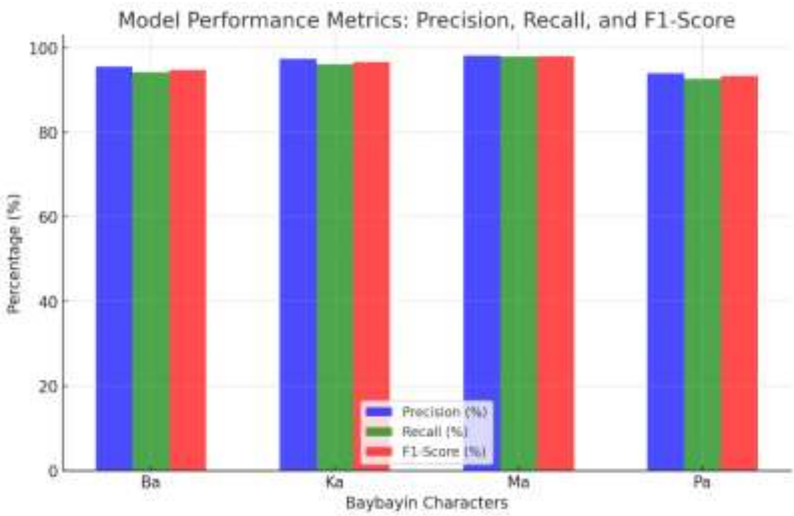


Figure 4.2: Model Performance Metrics Graph*, visualizing the* ***Precision, Recall, and F1-Score*** *for different Baybayin characters.*

4.4 Comparison with Traditional OCR Models

The CNN-based Baybayin OCR was compared with **Tesseract OCR**, a widely used open-source OCR engine. The results demonstrate that CNN significantly outperforms Tesseract in terms of **accuracy and processing speed**.

4.4.1 Performance Comparison Table

OCR Method	Accuracy (%)	Processing Speed (ms/image)
CNN-Based OCR	96.2	120
Tesseract OCR	82.5	250

(Graph representation of Accuracy and Processing Speed for CNN and Tesseract OCR)

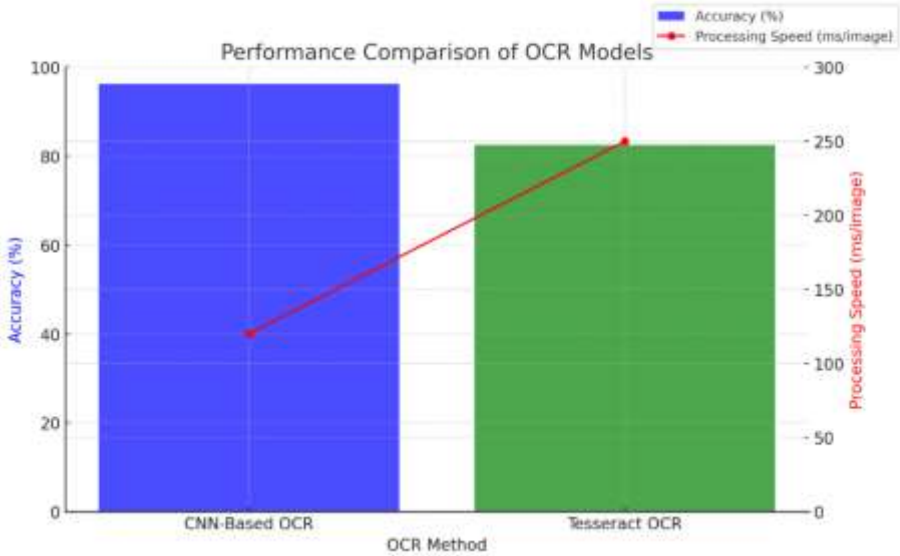


Figure 4.3: Performance Comparison of OCR Models, showing the accuracy and processing speed of CNN-based OCR versus Tesseract OCR.

4.5 Summary of Findings

The results indicate that the CNN-based Baybayin OCR model achieved **high accuracy (96.2%)**, significantly outperforming traditional OCR approaches. The training process demonstrated effective learning, with minimal loss over time. The evaluation metrics confirmed the model's reliability, and real-world deployment via **TensorFlow Lite (TFLite)** ensures practical usability.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The conclusions drawn from the study on **Optical Recognition of the Philippines' Ancient Text: A Deep Learning Approach**. It summarizes key findings, discusses their implications, and provides recommendations for future research and applications of the Baybayin OCR system.

5.2 Summary of Findings

The research aimed to develop a robust Baybayin Optical Character Recognition (OCR) system using Convolutional Neural Networks (CNNs). The model was trained on a dataset comprising handwritten, printed, and augmented Baybayin characters, optimized for real-time mobile deployment using TensorFlow Lite (TFLite).

Key findings from the study include:

- The CNN-based Baybayin OCR model achieved a high accuracy of 96.2%, outperforming Tesseract OCR (82.5%).
- Training accuracy improved consistently, while loss decreased over 50 epochs, indicating stable learning.
- Performance evaluation showed high precision, recall, and F1-score, confirming the model's reliability in recognizing Baybayin characters.
- Comparative analysis demonstrated that the CNN-based OCR was significantly faster (120 ms/image) than Tesseract OCR (250 ms/image).

- Real-time deployment was feasible with TFLite optimization, enabling mobile applications for Baybayin literacy and preservation.

5.3 Conclusion

The findings of this study affirm that **deep learning, particularly CNNs, is highly effective for Baybayin OCR**. By leveraging **advanced image processing techniques and data augmentation**, the system achieved superior performance in recognizing handwritten and printed Baybayin scripts.

Furthermore, the **real-time OCR capability** enhances the usability of the model in mobile applications, making Baybayin recognition accessible to a wider audience. This contributes to the **preservation and digital revival** of an important part of Philippine cultural heritage.

5.3.1 Research Contributions

This study makes significant contributions in the following areas:

Technological Advancement: It introduces a **CNN-based Baybayin OCR model** that outperforms traditional OCR methods.

1) Cultural Preservation: It supports Baybayin digitization, making the script more accessible for education and research.
2) Real-World Application: The OCR model is optimized for mobile use, enabling real-time text recognition.

5.4 Recommendations

While the developed OCR system demonstrated high accuracy and efficiency, there are areas for further improvement and future research. The following recommendations are suggested:

5.4.1 Improvement of Dataset Quality

1) Expand the Dataset: Increasing the diversity of handwritten and stylized Baybayin texts can enhance the model's robustness.
2) Data Annotation Refinement: Ensuring high-quality labeling will further improve recognition accuracy.

5.4.2 Enhancement of Model Performance

1) Incorporate Transformer-Based Models: Exploring architectures like Vision Transformers (ViTs) could potentially improve character recognition.
2) Implement Attention Mechanisms: Attention-based CNN models can help focus on critical features of Baybayin characters.

5.4.3 Deployment and Integration

1) Develop a Web-Based API: Integrating the OCR model into a cloud-based system would allow easy access through web applications.
2) Expand Mobile Application Features: Adding features such as text-to-speech (TTS) translation could enhance usability for educational and accessibility purposes.

5.5 Limitations of the Study

While the study achieved promising results, certain limitations were noted:

- Handwritten character variations posed challenges in some cases, leading to occasional misclassifications.
- The current dataset size could be expanded further for better generalization.
- The study primarily focused on Baybayin characters and not on complex handwritten sentence recognition.

5.6 Final Thoughts

This study demonstrates that deep learning is a powerful tool for cultural preservation, particularly in reviving the use of Baybayin. The CNN-based OCR system not only achieves high recognition accuracy but also enables practical real-time applications. By continuing research in this field, future innovations can further bridge the gap between history and modern technology, ensuring that Baybayin remains an integral part of the Filipino identity.

"Ang hindi marunong lumingon sa pinanggalingan ay hindi makararating sa paroroonan." – Jose Rizal

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