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A Period Prediction System for Sinhala Epigraphical Scripts using Ensemble CNNs and Attention Modules

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ABSTRACT

Identifying the period of epigraphical scripts is crucial for archaeologists and others to determine the age of inscriptions. Since different sets and shapes of letters were used in different eras, identifying the period of an epigraphical script also aids in recognizing these scripts. An ideal period prediction system should detect the era of an epigraphical script in real time with high accuracy. The objective of this study is to develop an automated system to predict the period of Sri Lankan Sinhala epigraphical scripts. In the first stage, a dataset of Sinhala epigraphical letter images was created using 7,012 samples from estampage pictures of Sri Lankan inscriptions, addressing the absence of a proper dataset. The proposed approach is more efficient than previous models as it can detect the period of individual letters as well as the period of raw, whole estampage images. Moreover, the approach incorporates a mechanism to detect the period of letters from inscriptions written between two consecutive eras. An ensemble CNN model with attention modules is utilized to identify the eras of epigraphical scripts. Experimental results show that the proposed system achieves an average classification accuracy of 93.88% in identifying the era of individual letters. The system can automatically determine the era of an inscription by analyzing its estampage image within thirty seconds.

Article information:

Keywords: Ensemble CNNs, Period Prediction, Sinhala Character Recognition, Sri Lankan Inscriptions, Epigraphical Scripts

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1. INTRODUCTION

Inscriptions are essential for understanding the past history of any civilization, and they are typically written on slabs, stones, and cave surfaces. They are most commonly found in Greek, Latin, and many South Asian countries, including Sri Lanka and India. The study of inscriptions is called epigraphy, and all forms of writing found in inscriptions are referred to as epigraphical scripts. The analysis of epigraphical scripts is crucial for any civilization, as they contain evidence of ancient social, cultural, religious, political, administrative, linguistic, and economic practices. Consequently, they are regarded as one of the primary sources in archaeology.

In most ancient languages, the shapes of their letters underwent reform over the centuries, and different groups of letters were used in various periods. Therefore, recognizing the epigraphical scripts of an ancient language can be a challenging problem. In this context, automated handwritten inscription character recognition systems are considered crucial for identifying the set of letters of an ancient language in a particular era, thereby facilitating the identification of epigraphical scripts from specific periods as an essential preliminary task. Additionally, period prediction is vital for archaeologists as they use it to determine the era of an inscription based on its letter set. Hence, automated period prediction systems [1-6, 8, 9, 11] are essential for understanding epigraphical scripts. They aim to determine the period of an ancient script based on the groups of letters and their shapes found within inscriptions of ancient languages.

Sri Lanka has a long history [12] of human settlement, with over 4,000 discovered inscriptions to date. Based on their location and appearance, Sri Lankan inscriptions are classified into four types: rock, cave, pillar, and slab inscriptions [13-15]. Sinhala and Tamil are ancient languages of Sri Lanka, and their

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epigraphical scripts are found in several locations throughout the country, including Polonnaruwa, Mihintale, and Ritigala. One of the most famous Sri Lankan inscriptions, 'Galpotha' is shown in Fig. 1. Although some researchers have already worked on identifying Sinhala letters from Sri Lankan inscriptions, no period prediction methods have been developed to categorize Sri Lankan epigraphical scripts. Therefore, there is a need for such methods or techniques to support Sri Lankan historians and archaeologists.

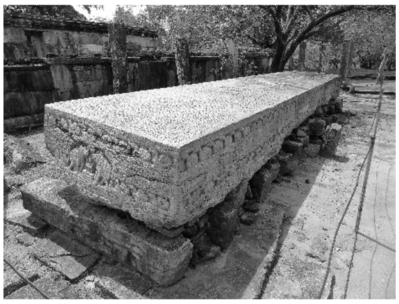

Fig.1: *"Galpotha" stone inscription. (Photo taken by Cherubino).*

The ancestors of the Sinhala language are the Brahmi scripts, which also serve as the ancestor of many other South Asian languages, including Prakrit, Tamil, Kannada, Saka, and Tocharian [16]. These languages developed through the evolutionary changes of the Brahmi writing system in various regions. The evolution of the Sinhala alphabet is divided into five distinct periods: Early Brahmi Period, Later Brahmi Period, Transitional Brahmi Period, Medieval Sinhala Period, and Modern Sinhala Period. [14, 17, 18]. Table 1 provides the evolutionary periods of the Sinhala alphabet.

Table 1: *Classification of the Sinhala alphabet based on their evolutionary periods.*

Period	Time Duration
Early Brahmi	Third century BC to First century AD
Later Brahmi	First century AD to Third century AD
Transitional Brahmi	Fourth century AD to Seventh century AD
Medieval Sinhala	Eighth century AD to Eleventh century AD
Modern Sinhala	Twelfth century AD to the Present

During the Early Brahmi Period, the Sinhala alphabet originated from Brahmi scripts. Although ancient Brahmi had 38 letters, only 25 were used in Sri Lanka during this period [14, 19]. Throughout the evolution of the Sinhala alphabet, many new letters and symbols were introduced, including unique sound letters such as nasal sounds [19, 20]. The modern Sinhala alphabet has 60 letters. Fig. 2 shows the evolution of some letters in the Sinhala alphabet, showcasing different shapes of characters used in different eras for a particular alphabet letter.

Fig.2: *Evolution of some Sinhala alphabet letters through different periods.*

Extracting text from inscriptions is challenging due to their varying locations and sizes. Estampage [16, 21] is a well-known stamping technique in archaeology used to make an identical copy of an inscription. In this procedure, an exact image of an inscription is extracted onto an inked paper and then dried to analyze the shape of the letters. In estampage papers, the alphabet letters appear in white, while the background is black. Researchers [15, 24, 25, 28] often use images of estampage papers in recognition and period prediction tasks because they provide more accurate representations of inscriptions than photographic images. To the best of our knowledge, there are no well-structured image datasets available for Sri Lankan inscriptions or estampages, which are crucial for computational archaeology.

Over the past few years, several approaches [1-3, 5, 6, 8] have been proposed to predict the era of inscriptions using the age of epigraphical scripts. Although traditional machine learning techniques were used in previous approaches, recent methods rely on deep learning algorithms, especially Convolutional Neural Networks (CNNs) [22], for recognizing epigraphical scripts [10, 23-25] and performing period prediction tasks.

Developing a period prediction system for Sinhala epigraphical scripts is challenging due to several factors. Most of the surfaces of Sri Lankan inscriptions are partially damaged, resulting in broken and noisy alphabet letters in the corresponding estampage papers. Additionally, the orientation and shape of the inscriptions cause pose variations and appearance changes in the extracted letters of epigraphical scripts. Therefore, an automated Sinhala period prediction system must address these challenges.

An efficient automated period prediction approach should be able to identify the period of an inscription from the epigraphical script with state-of-the-art accuracy and real time detection speed. To achieve these goals, we propose an automated method for predicting the period of Sri Lankan Sinhala inscriptions. In the first step of our approach, estampage images were obtained from various locations in Sri Lanka. Next, the alphabet letters were extracted, and a series of preprocessing techniques were applied to create a dataset of images representing ancient Sinhala alphabet letters. In the next phase, three pre-trained CNNs individually train the period prediction classifier. In addition, a channel-spatial attention module is incorporated into these models to improve classification performance. Finally, the performance of these three CNNs is ensembled using a majority voting-based technique. Based on the testing results, the proposed system can identify the period of a Sri Lankan inscription with 93.88% accuracy. Our study has two main contributions:

- We built an image dataset of ancient Sinhala alphabet letters from ancient Sri Lankan inscriptions and their corresponding estampages. The dataset includes a total of 7,012 images of alphabet letters. To our knowledge, no previous datasets have been built for Sinhala alphabets.

- Our proposed classification model achieved an outstanding accuracy of 93.88% and can predict the era of an inscription in real time.

We extended our preliminary work [26] by including a spatial-channel attention module in the CNN model architecture, which improved the average accuracy from 90.60% to 93.88%. Additionally, we expanded the dataset by including 1,852 additional image samples and tested the proposed system in an automated, end-to-end manner. The rest of this manuscript is organized as follows: Related Work, Background, Methodology, Results and Discussion, and Conclusion.

2. RELATED WORK

Over the past few years, a considerable number of period prediction approaches have been proposed to predict the era of epigraphical scripts and inscriptions using machine learning or deep learning, as well as computer vision-based algorithms.

Over the past decade, several methods have been proposed to predict the era of inscriptions based on the evolution of epigraphical scripts. Heenkenda and Fernando [37] proposed a deep-learning approach to classify Sinhalese inscriptions into five periods based on paleographical and morphological data. They used raw images from a dataset of 475 images from 62 inscriptions, without performing a character-wise analysis of the alphabets from each period. Their findings showed inscription classification accuracies ranging from 57.44% to 85.94%, with the Inception-v3 model performing best. Bhat and Achar [4] proposed a period prediction system for Kannada epigraphical scripts using an image segmentation technique to extract the Kannada alphabet letters from stone inscription images, followed by a template matching technique to identify the era of an inscription. Soumya and Kumar [5] initially used a Support Vector Machine (SVM) classifier with regional image features to predict the period of Kannada epigraphical scripts. They later improved their model [6] by using a Random Forest (RF) classifier. Bannigidad and Gudada [7] proposed a similar method for ancient Kannada handwritten scripts using Local Binary Patterns (LBP) features and an SVM classifier. Gangamma et al. [3] proposed a period prediction approach for Kannada scripts using curvelet transform features and a K-Nearest Neighbour (K-NN) classifier. Bannigidad and Gudada [8] proposed a similar approach for Kannada ancient handwritten scripts using Histogram of Oriented Gradients (HOG) features and a K-NN classifier. Mohana and Rajithkumar [11] used basic image-processing techniques and statistical feature-matching techniques to detect the period of Kannada scripts. Kumar and Poornima [2] proposed a method to predict the era of Tamil epigraphical scripts using South Indian inscription im-

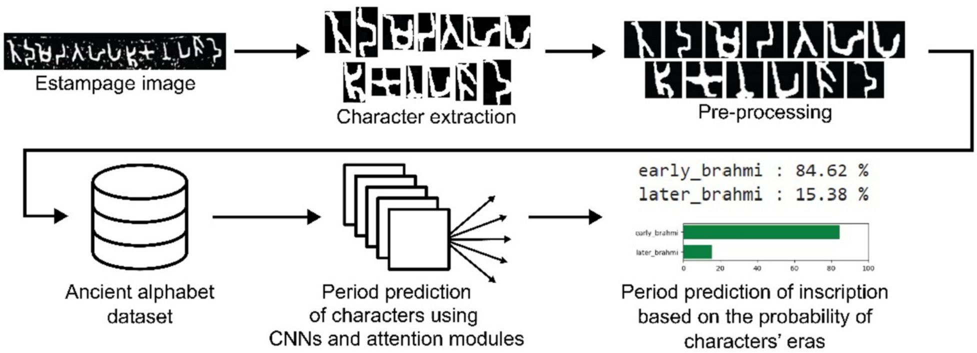

Fig.3: Outline of the proposed method.

ages. They extracted regional features and used an SVM classifier for the classification. Subashini *et al.* [1] proposed another similar Tamil period prediction approach using local image features and an SVM classifier. Recently, Savaridass et al. [9] proposed a CNN-based approach for classifying ancient Tamil scripts in palm-leaf manuscripts. Klassen et al. [10] proposed a semi-supervised approach to predict the era of Cambodian scripts and inscription images. However, the accuracy of these methods for period prediction is quite low, as most depend on handcrafted image features and traditional machine learning algorithms. As a result, they fail to capture the shape variations of letters and are not robust enough to distinguish between alphabet sets with similar shapes.

In the past few years, several approaches have been proposed to enhance various computational archaeological tasks in Sri Lanka, such as optical character recognition (OCR) and translation. Karunarathne *et al.* [24] trained a CNN to identify ancient Sinhala letters in an inscription image, considering only nine letters and 85 samples in their study. Bandara *et al.* [14] proposed a method to create fonts of the early Brahmi period by feeding images of inscriptions. They then used those fonts to automatically read ancient Sri Lankan inscriptions. Warnajith *et al.* [27] also used a similar approach to detect early Brahmi letters. Wijerathna *et al.* [25] proposed a CNN architecture to recognize Sinhala scripts from the early Brahmi period and then translate them to modern Sinhala letters using natural language processing (NLP) algorithms. Ruwanmini *et al.* [28] used Sri Lankan estampage paper images to develop an inscription character dataset and then created an OCR module using the K-means clustering algorithm. Recently, Ruwanmini et al. [38] proposed a deep-learning approach for Sinhala inscription character recognition. According to their findings, using a CNN in identifying ancient characters on smoothed images resulted in an accuracy of 95%. Overall, the recognition performance of these approaches is considerably inadequate since their systems were developed for a particular evolutionary period of the Sinhala alphabet (mainly the early Brahmi period), and their created datasets have a limited number of samples (less than 100).

Predicting the period of an epigraphical script is crucial for recognizing ancient characters, as each era used distinct sets and shapes of letters. Additionally, a period prediction system should be capable of identifying the era of an inscription in real time based on the character sets. Although a few researchers have proposed models to recognize ancient Sinhala scripts, all of them have been developed to identify early Brahmi letters. Furthermore, most of these models struggle to achieve better recognition performance due to a deficiency in training data. In this context, we aim to develop an automated period prediction system for the Sinhala alphabet using an end-to-end deep learning approach. Additionally, we aim to construct a comprehensive ancient Sinhala letters dataset that includes character sets from all five evolutionary periods, which is crucial for developing period prediction and OCR systems.

3. METHODOLOGY

In this study, we propose an automated system to predict the period of Sri Lankan Sinhala inscriptions based on their epigraphical scripts. The proposed system automatically segments the letters from inscription images. It is then able to classify the ancient letters into five periods: early Brahmi, later Brahmi, transitional Brahmi, medieval Sinhala, and modern Sinhala. A Sinhala ancient alphabet letters' image dataset has been built in this study. To create the dataset, we collect several estampage images of Sri Lankan inscriptions, manually extract the alphabet letters, and partition them into test and training sets. The individual letters are labeled with the assistance of experts from the Department of Archaeology, Sri Lanka. In the next stage of the proposed methodology, a deep transfer learning mechanism is employed to fine-tune three pre-trained CNN models for classifying the era of alphabet letters. Additionally, an attention mechanism is utilized to enhance the classi-

Fig.4: *Illustration of Sinhala alphabet letters extraction and preprocessing.*

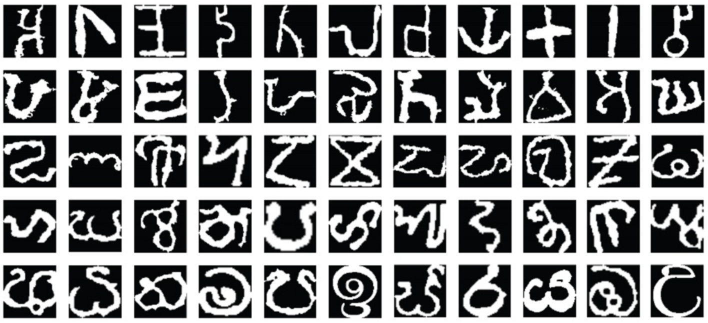

Fig.5: *A few samples of the Sinhala alphabet letter image dataset. The rows from top to bottom show sample images from Early Brahmi, Later Brahmi, Transitional Brahmi, Medieval Sinhala, and Modern Sinhala.*

fication performance of the proposed system. Based on the predicted period of individual letters, the era of an inscription is identified. The outline of the proposed methodology is shown in Fig. 3. Each step of the proposed method is explained in detail as follows:

3.1 Collection of Estampage Images

At the beginning of this study, we collected Sinhala estampage images. Most of these images were obtained from the Department of Archaeology, Anuradhapura regional office in Sri Lanka, while a few were sourced from various other references [29, 31, 32]. We also collected printed epigraphy and stone plaque images from the modern Sinhala period. A total of 175 inscriptions from various locations in Sri Lanka were used in this study. With the assistance of archaeological research and development officers, the collected image samples were classified into five eras.

3.2 Sinhala Alphabet Letters Extraction

We manually extracted individual letter images from the estampage images to train a machine-learning model. A total of 128 inscription estampage pictures were used to extract the individual letter images, while the remaining images were used to test the model in an automated manner. We manually cropped the letters using the GNU Image Manipulation Program (GIMP). Fig. 4 (first column) shows a few examples of the cropped images.

3.3 Preprocessing of Sinhala Alphabet Letter Images

The cropped Sinhala alphabet letter images vary in size due to their different shapes. Additionally, some pictures have a white background and black foreground. Furthermore, since many of the estampage images contain noise, many letter images were cropped with noise. To address this, we applied a series of automated image preprocessing techniques to enhance the quality of the individual letter images.

In the first stage of preprocessing, the images were converted to grayscale, and the Non-Local Means denoising algorithm [33] was applied to remove noise. Then, we applied a Gaussian blur to smooth the letter shapes. Afterward, a threshold function was used to convert the images into binary images. To ensure a consistent format for all letter images, white backgrounds were inverted to black using the image negative operation. A few sample images after this step are shown in Fig. 4 (second column).

In the next stage of preprocessing, we kept the most prominent white blob and removed the remaining blobs and background using morphological image processing techniques, as shown in Fig. 4 (third column). Finally, all individual letter images were resized to 64 × 64 pixels while maintaining their original aspect ratio, as shown in Fig. 4 (fourth column).

3.4 Construction of Sinhala Alphabet Letter Image Dataset

In the next stage of this study, we constructed a dataset of ancient Sinhala letters from pre-processed images. The images of all ancient letters were labeled into five eras based on their inscription period. In each era, 80% of the images were assigned to the training set, and the remaining pictures were transferred to the test set. 7,012 images were labeled, and their details are summarized in Table 2. Fig. 5 shows some sample images from the dataset. This dataset will be valid for various research tasks, including ancient Sinhala character recognition.

Table 2: *Details of the Images in the Dataset.*

Period	Training Samples	Testing Samples
Early Brahmi	1322	332
Later Brahmi	609	153
Transitional Brahmi	504	126
Medieval Sinhala	1203	301
Modern Sinhala	1969	493

In the constructed dataset, different sets and quantities of alphabet letters were used for various eras. Although the dataset includes 1,654 images from the early Brahmi period, these images represent 25 individual alphabet letters from that time. As stated in Table 3, the average number of distinct letters in-

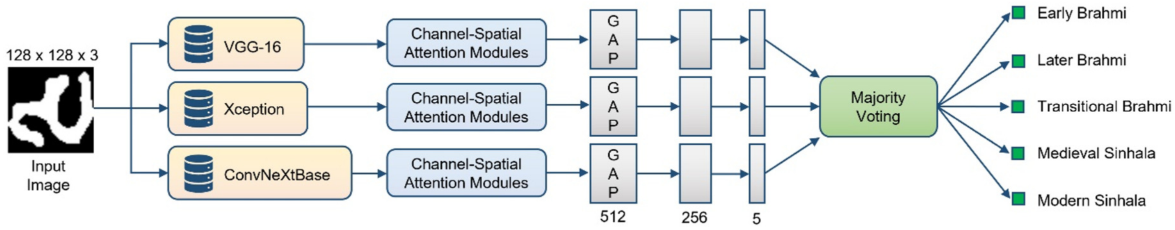

Fig.6: *Block diagram of the proposed ensemble CNN model. Pre-trained architectures are modified by including the GAP layer and used as the backbone network. The final classification result is obtained by using majority voting.*

creased over time, from 25 in the early Brahmi period to 60 in the Modern Sinhala period. In the constructed dataset, the shapes of some letters from earlier periods evolved with the addition of vowels to consonants. Additionally, many new letters were introduced over time, while certain letters from earlier periods are absent in subsequent periods. Furthermore, no particular mechanism was employed to balance the letter frequencies within a period, as all the undistorted letters were extracted from inscriptions without considering their frequency of appearance.

Table 3: *Details of Individual Letters in the Dataset.*

Period	No. of image samples	Average No. of individual alphabet letters
Early Brahmi	1654	25
Later Brahmi	762	25
Transitional Brahmi	630	30
Medieval Sinhala	1504	40
Modern Sinhala	2462	60

The construction of the dataset allowed us to observe several noticeable patterns in Sinhala alphabet letters. During the Early Brahmi and Later Brahmi periods, alphabet letters were simple in shape and had many straight lines. However, as the Sinhala language evolved, alphabet letters became increasingly complex and varied in shape during the Medieval Sinhala and Modern Sinhala periods. Additionally, we noticed that the number of pixels in a letter's image increased over the evolution of the Sinhala language, as the length of individual letters increased from the Early Brahmi to the Modern Sinhala period.

3.5 Data Augmentation

In the next stage of this study, we generated additional image samples using data augmentation techniques to address imbalanced classification and to improve the generalization capability. Specifically, for each ancient Sinhala letter image, we generated seven new samples by applying various transformations, including zooming, horizontal and vertical flipping, rotation, shearing, and shifting in width and height.

3.6 Proposed CNN Architectures

In this study, three CNN models were trained individually to classify the estampage Sinhala alphabet letter images. These models take 128 × 128 images of the alphabet letters as input and output the classification scores for five periods.

We utilized the VGG-16 [30], Xception [35], and ConvNeXtBase [36] models as the baseline networks to train the classifiers. These pre-trained baseline CNN models are modified for period prediction to achieve maximum performance with the few available training samples. As the first step of modification, all fully connected layers are removed from these pre-trained models, and a combined channel-spatial attention module is included to enhance classification performance. As shown in Fig. 6, the proposed attention modules consume the last convolutional features and output the refined features with the same dimension. The architecture of the proposed attention modules is illustrated in Fig. 7.

The channel attention module highlights the most significant features across different channels, while the spatial attention module focuses on the most relevant regions within the spatial dimensions. We have combined them to provide a more comprehensive attention mechanism. In the proposed work, the channel attention module first identifies and enhances important feature channels, and then the spatial attention module focuses on the significant spatial regions within those channels.

As shown in Fig. 7, The proposed channel attention module obtains the features (X) of the last convolutional layer with a size of $8 \times 8 \times 512$. Global Average Pooling (GAP) and Global Max Pooling (GMAX) operations are simultaneously performed on X to remove spatial information. These operations capture the feature's presence across the entire spatial dimensions and highlight its strongest occurrence at any specific location. GAP and GMAX operations produce outputs with dimensions of $1 \times 1 \times 512$. Next, the channel-wise dependencies of these features are learned by two fully connected layers, producing outputs with sizes of $1 \times 1 \times 32$ and $1 \times 1 \times 512$. We used the Swish activation function [34] in these fully connected layers, as it is smoother than other activation func-

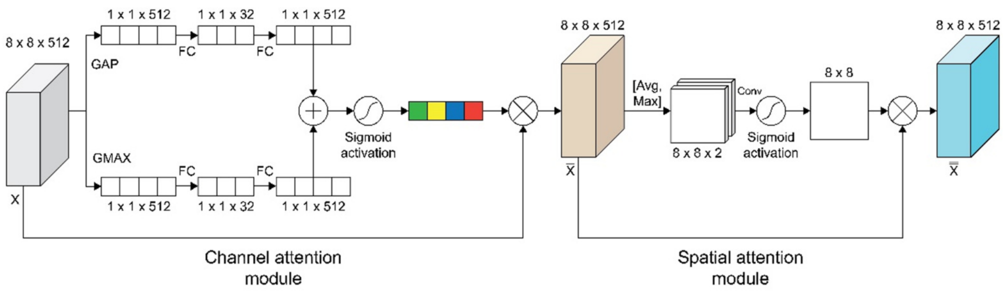

Fig. 7: *The architecture of the channel attention and the spatial attention modules. It consumes the last convolutional layer's features with the size of 8 × 8 × 512 and outputs same dimension refined features.*

tions. The outputs of these two branches are then added using an element-wise summation operation to produce the channel attention map with a size of $1{\times}1{\times}512$. Finally, the Sigmoid activation function is used to activate the channel attention, which is then multiplied with the input convolutional features using an element-wise multiplication operation to produce the channel-wise refined features $\bar{\mathrm{X}}$.

The proposed spatial attention module obtains feature $\bar{\mathrm{X}}$ from the channel attention module and performs average and max pooling operations along the channel axis. The outputs of these two operations are concatenated to produce a feature map with a size of $8{\times}8{\times}2$. Next, a convolutional layer with a $3{\times}3$ kernel is used to generate a spatial attention map with a size of $8{\times}8$. Finally, the Sigmoid activation function is applied to activate the spatial attention, and the output feature $\bar{\bar{\mathrm{X}}}$ is obtained by multiplying the spatial attention and $\bar{\mathrm{X}}$ using a channel-wise multiplication operation.

After the combined attention modules, a Global Average Pooling (GAP) layer is employed at the end of each CNN classifier instead of the flatten operation. This GAP reduces the number of parameters, allowing the model to train with fewer samples. After the GAP layer, two fully connected layers are included, with 256 and 5 neurons, respectively.

3.7 Training CNN Models

In the proposed approach, all three CNN classifiers are individually trained using the Adam optimizer with the training image samples. During training, most of the early convolutional layers of each model are not trained to mitigate the risk of overfitting. The categorical cross-entropy loss is used to train the models. A cosine decay learning rate scheduler is used to further enhance the training process.

During training, the hyperparameters of individual CNN models, and then the ensemble model, were fine-tuned to optimize classification performance. Several hyperparameters were fine-tuned for each CNN, including batch size, optimizer, number of training iterations, learning rate, and the number of neurons in fully connected layers. The performance of the individual CNNs was measured for batch sizes 16, 32, and 64, with 32 being chosen based on the experimental results. Additionally, these models were trained for 100 epochs, and the best model was selected based on the highest validation accuracy between 50 and 100 epochs. Similarly, the initial learning rate of these CNN models was tested with various values, and a learning rate of 0.0002 was selected based on the validation results. Based on the experimental results, the first fully connected layer was configured with 256 neurons. Furthermore, the performance of these models was evaluated using Adam, SGD (Stochastic Gradient Descent), and RMSprop optimizers, with Adam being selected based on the experimental results. The training process is conducted for a fixed number of iterations, and based on the validation accuracy, training is stopped prematurely to prevent overfitting.

In addition to the hyper-parameter tuning of individual models, the hyper-parameters of the combined ensemble model are also tuned. To optimize the performance of the ensemble model, various voting schemes, such as majority voting and weighted voting, were evaluated. Based on the experimental results, the majority voting scheme was selected.

3.8 Period Predictions Using Majority Voting

In the final part of the proposed methodology, the periods of the estampage Sinhala alphabet letter images are predicted by combining the classification scores of all three CNN models. In the first step of prediction, individual model classification scores for a test image are obtained from the three CNN models. The final classification result is then determined by selecting the class label that receives the most votes across all three models. The proposed majority voting-based period prediction method is simple and fast, requiring no additional training or parameter tuning. We treat all three models equally in this majority voting-based prediction approach.

3.9 Testing Performance Using Individual Alphabet Letter Images and Whole Estampage Images

The period prediction performance of the proposed model is tested in two stages in this study. In the first stage, the test set comprises individual Sinhala alphabet letter images fed to the proposed CNN models, and their prediction performance is measured. A total of 1,405 individual Sinhala alphabet letter images are used in this testing stage. In the second stage, the entire estampage image of an inscription is input into the proposed system, and the period prediction performance is evaluated end-to-end. A total of 48 raw estampage images, which were not used to create the Sinhala alphabet individual letter image dataset, were used in the second stage of testing.

To conduct the end-to-end testing in the second stage, all steps of the proposed method are automated, including segmenting the individual letters from the whole estampage image and preprocessing the alphabet letters. In the first step of automated end-to-end testing, the raw estampage image is converted to grayscale. Then, non-local means of denoising and Gaussian blur are applied to the image to eliminate noise. After denoising, the grayscale estampage image is converted to a binary image using a thresholding function. Next, the individual alphabet letters are segmented from the binary estampage image by detecting the contours of the letters. During this automated segmentation process, some noise blobs are also identified but are automatically removed based on their aspect ratio and the ratio between white and black pixels. After the segmentation stage, all individual alphabet letter images are preprocessed and resized to a fixed size as described in Section 3.3 of the methodology and then input to the CNN models. As the final step of end-to-end testing, the period of a whole estampage image is predicted based on the majority era of its letters.

In some inscriptions, most letters belong to a particular period, while a minority of letters belong to a successive period. This variation occurs when the inscriptions were written during a time close to the transition between two successive periods of evolution. Such inscriptions are identified if less than 85% of individual alphabet letters belong to one period while the remaining letters belong to another consecutive period. For inscriptions spanning successive periods, the final test results report the two most common periods for the individual letters.

4. RESULT AND DISCUSSION

4.1 Implementation Details

We utilized the Google Colab cloud platform for implementation. All the experiments were conducted on an NVIDIA K80 GPU using the Keras and TensorFlow libraries. The proposed model was trained for 100 iterations using the Adam optimizer. The implementation code for this study is publicly available at (`https://github.com/pabasar/epigraphy-period-ens-cnn`).

4.2 Evaluation Protocols

The classification accuracy, precision, recall, and F1-score are used to measure the performance of the proposed approach. These evaluation metrics are calculated using the following equations:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$precision = \frac{TP}{TP+FP} \tag{2}$$

$$recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall} \tag{4}$$

In these equations, TP stands for true positives, FP for false positives, TN for true negatives, and FN for false negatives. In addition to these metrics, we have calculated the automated segmentation performance of the proposed approach using the following equation:

$$segmenting\ accuracy = \frac{segmented\ letters}{all\ letters} \tag{5}$$

In this equation, 'all letters' denotes the count of the entire alphabet letters in an input estampage image, and 'segmented letters' represents the number of letters successfully segmented from that input image. In addition to segmentation accuracy, we have evaluated the segmentation performance of the proposed approach using Pixel Accuracy (PA), as defined by the following equation:

$$PA = \frac{No.\ of\ Correctly\ segmented\ pixels}{Total\ no.\ of\ pixels\ in\ the\ image} \tag{6}$$

We have measured the Pixel Accuracy for each and every estampage image by comparing the segmented output with the corresponding ground truth mask. Finally, the Overall Pixel Accuracy (OPA) of entire estampage images is calculated as follows:

$$OPA = \frac{\sum_{i=1}^{n} PA_i}{n} \tag{7}$$

Where 'n' is the total number of estampage images in the test set.

4.3 Ablation Studies

The performance of the proposed approach mainly relies on the ensemble models and attention modules.

Therefore, we conducted an ablation study to justify the design of the proposed period prediction model. We evaluated the test set of the Sinhala individual letters image dataset and used the average classification accuracy to measure performance.

The proposed period classification model combines the performance of three CNN classifiers using a majority voting-based ensemble technique. The individual classification performance of these three models is given in Table 4. Among the three models, the VGG-16-based model performed better than the others because of its simplicity and flexibility for downstream tasks. As shown by the experimental results, combining the classification performances increases the average classification accuracy by 1.85% compared to the results of VGG-16.

Table 4: *Performance comparison of each model and the ensemble.*

Model	Accuracy (%)
VGG-16	92.03
Xception	89.40
ConvNeXtBase	87.12
Ensemble	93.88

The channel and spatial attention modules were utilized in the proposed approach to boost classification performance. A comparison study was conducted to demonstrate the effectiveness of the channel and spatial attention modules in period prediction, and the results are shown in Table 5. The experimental results clearly demonstrate that incorporating both channel and spatial attention in each CNN model outperforms using either one alone.

Table 5: *Performance comparison of Attention Modules.*

Architecture	Average classification Accuracy (%)
Ensemble CNN models without any attention modules	91.25
Ensemble CNN models with channel attention modules	92.46
Ensemble CNN models with spatial attention modules	92.81
Ensemble CNN models with channel and spatial attention modules	93.88

4.4 Testing Results

The period prediction performance of the proposed approach was evaluated in two stages, as mentioned in the methodology: using the test set of individual alphabet letter images and using whole estampage images in an end-to-end manner. The experimental results of the first testing stage are summarized in Table 6, utilizing 1405 individual Sinhala alphabet letter images.

Table 6: *Test results of Individual Alphabet Letter Images. The abbreviations are as follows: Pre. - Precision, Rec. - Recall, EB - Early Brahmi, LB - Later Brahmi, TB - Transitional Brahmi, MED - Medieval Sinhala, and MOD - Modern Sinhala.*

Period	Pre. (%)	Rec. (%)	F1-Score (%)	Average Classification Accuracy (%)
EB	96	95	95	93.88
LB	85	90	87	
TB	84	88	86	
MED	95	91	93	
MOD	97	98	97	

Our proposed model showed an average classification accuracy of 93.88% on the individual letter image dataset. The confusion matrix for the 1,405 test samples is given in Table 7.

Table 7: *Confusion matrix of individual letter image classification. The abbreviations are as follows: EB - Early Brahmi, LB - Later Brahmi, TB - Transitional Brahmi, MED - Medieval Sinhala, MOD - Modern Sinhala, TL - True Labels, and PL - Predicted Labels.*

TL\PL	EB	LB	TB	MED	MOD
EB	314	13	3	2	0
LB	8	137	6	2	0
TB	1	10	111	2	2
MED	2	0	11	275	13
MOD	2	1	1	7	482

In the second stage of testing, 48 raw whole estampage images were used, and the proposed approach successfully identified their period with an average segmentation accuracy of 95.23% and an overall pixel segmentation accuracy of 82.91%. The experimental results of all whole estampage images are individually reported in Table 8. As stated in the methodology, some inscriptions were written in an era closer to the boundary of two consecutive periods. Hence, some letters belong to one period while the remaining belong to the other successive period. For these inscriptions, the first and second most majority periods are reported, as shown in Fig. 8.

Table 8: *Results of raw whole estampage images using end-to-end testing. The abbreviations are as follows: EB - Early Brahmi, LB - Later Brahmi, TB - Transitional Brahmi, MED - Medieval Sinhala, and MOD - Modern Sinhala.*

Image No.	Actual Periods	Predicted Period (%)	Misclassification (%)
1	3rd BC - 1st AD	EB: 63.64 LB: 36.36	None
2		EB: 85.71	14.29
3		EB: 93.75	6.25
4		EB: 100	None

5		EB: 84.62% LB: 7.69	7.69
6		EB: 100	None
7		EB: 88.89	11.11
8		EB: 100	None
9		EB: 77.78 LB: 11.11	11.11
10		EB: 100	None
11		EB: 90	10
12		EB: 87.5	12.5
13		EB: 77.78 LB: 11.11	11.11
14		EB: 84.62 LB: 15.38	None
15		EB: 71.43 LB: 28.57	None
16		EB: 100	None
17		EB: 66.67	33.33
18		EB: 100	None
19	2nd BC	EB: 100	None
20		EB: 83.33 LB: 16.67	None
21	1st BC	EB: 70.37 LB: 25.93	3.7
22	1st AD	LB: 39.13 EB: 26.09	34.78
23		LB: 100	None
24	1st – 3rd AD	LB: 64 EB: 20	16
25		LB: 100	None
26	2nd AD	LB: 31.25 EB: 18.75	50
27		LB: 65.71 EB: 22.86	11.43
28	3rd AD	LB: 84.21 TB: 15.79	None
29	3rd – 4th AD	LB: 84.21 TB: 15.79	None
30		TB: 70.0 MED: 30.0	None
31	4th AD	LB: 78.92	21.08
32		TB: 60	40
33	4th – 5th AD	LB: 37.5 TB: 37.5	25
34	5th AD	TB: 65.52 LB: 13.79	20.69
35		TB: 61.29 LB: 17.74	20.97
36		TB: 63.16 MED: 21.05	15.79
37	10th – 11th AD	MED: 62.5	37.5
38	12th AD	MED: 50 MOD: 36.36	13.64
39		MED: 64.1 MOD: 35.9	None
40		MED: 56.25 MOD: 43.75	None
41		MED: 59.26 MOD: 40.74	None
42		MED: 49.18 MOD: 42.62	8.2
43		MOD: 70 MED: 25	5
44		MOD: 74.07	25.93
45		MOD: 55 MED: 35	10
46		M0D: 78.57 MED: 14.29	7.14
47	16th AD	MOD: 92.31	7.69
48	19th AD	MOD: 93.75	6.25

Although no previous approaches have been proposed to identify the period of Sinhala inscriptions, we have also compared the performance of the proposed approach with similar period prediction approaches proposed for other languages. Although these similar approaches differ from one another based on the number of classes and the number of test images, we have considered their average classification accuracy and summarized the results in Table 9.

4.5 Discussion and Future Directions

This study proposes an automated period prediction system for Sri Lankan Sinhala inscriptions and demonstrates outstanding performance on the test set of the dataset.

The proposed work is more significant and vital than previous period prediction approaches in several ways. Almost all prior approaches could only identify the period f an inscription and its corresponding script by examining individual letters, which is not practically useful for archaeologists and others. In contrast, the proposed study takes an entire estampage as input and predicts its period in an end-to-end manner. Additionally, the proposed approach automatically processes the entire estampage as a whole, extracting individual letters in real time. It then predicts the period of the inscription by analyzing each letter individually. This method enhances accuracy by automating both the extraction and prediction processes, effectively addressing the limitations of previous methods that relied on manual extraction or struggled to analyze complete estampages. Moreover, none of the earlier approaches include a specific mechanism to identify the period of letters from inscriptions written between two consecutive eras. The

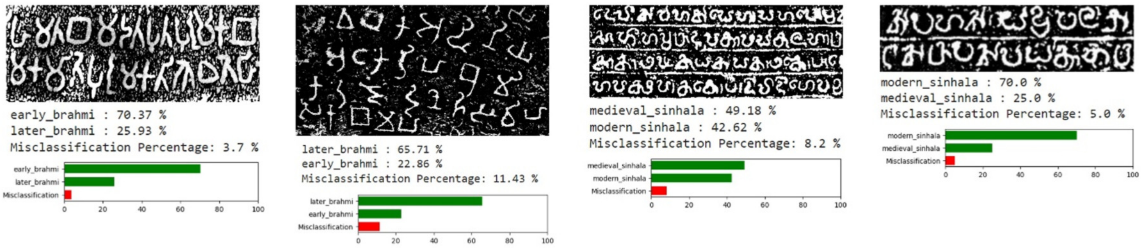

Fig.8: *An illustration of the results from inscription-wise, automated, end-to-end predictions. The graph shows the percentages of predicted periods with green bars and misclassifications with a red bar.*

Table 9: *Comparison of the proposed approach with other period prediction studies. N/G denotes Not Given.*

Study	No. of Periods	Algorithm	Overall Accuracy
[1]	4	Support Vector Machine	88.45
[5]	9	Support Vector Machine	N/G
[3]	6	Fast Discrete Curvelet Transform	85.78
[6]	6	Random Forest	85.00
[2]	3	Transductive Support Vector Machine	94.66
[11]	2	Mean and Sum of Absolute Differences	99.20
[4]	4	The sum of Absolute	80.00
[7]	3	Latent Dirichlet Allocation, K-Nearest Neighbors, Support Vector Machine	99.30
[8]	4	K-Nearest Neighbors, Support Vector Machine	96.70
[37]	5	CNNs	85.94
Proposed Approach	5	Ensemble CNNs and Attention Modules	93.88

proposed study successfully addresses this gap by employing a mechanism to identify the period of letters from such inscriptions.

Based on the experimental results, the proposed approach showed poorer classification performance for the Transitional Brahmi and Later Brahmi periods compared to other eras. The reduced performance may be due to the limited number of training samples for these periods and the lower frequency of period-specific letters compared to other eras. Additionally, during the transitional Brahmi era, the Sinhala script evolved from Brahmi to Sinhala, introducing a wide range of new shapes in transitional Brahmi, which makes recognition more challenging.

The proposed approach focuses on spatial features for period prediction using CNNs. However, the sequence of letters, such as the flow of characters or words in an inscription, is also crucial for accurately detecting their period. In future work, we plan to develop a hybrid architecture that utilizes CNNs alongside RNNs or Transformers to capture spatial and sequential features, thereby enhancing period prediction.

In addition to the Asian region, epigraphical scripts can be found around the globe in areas where civilizations have existed, especially in the Arabian Peninsula and Europe. As future directions for this study, researchers can generalize the proposed methodology for period prediction of other languages around the globe. Additionally, treating period prediction as a preliminary step allows optical character recognition to be applied to the alphabetic letters specific to each period, integrating natural language processing techniques. This approach enables the extraction of information from the inscription, which will aid archaeologists in reconstructing the history of newly discovered inscriptions.

5. CONCLUSION

In this study, an automated period prediction system was proposed to identify the age of Sri Lankan Sinhala epigraphical scripts. A large dataset of ancient letter images was constructed, comprising 7,012 individual letter images and 48 raw whole estampage images. An ensemble CNN classifier was developed using the VGG-16, Xception, and ConvNeXtBase pre-trained models. Channel and spatial attention modules were utilized to enhance classification performance further. The proposed system can detect the period of a raw estampage image of an inscription within thirty seconds, achieving an average segmentation accuracy of 95.23%, an overall pixel segmentation accuracy of 82.91%, and an individual letter period prediction accuracy of 93.88%. Additionally, the system is globally applicable and can be generalized for period prediction of scripts in other languages based on the availability of estampage images.

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AUTHOR CONTRIBUTIONS

Conceptualization, Pabasara Surasinghe, and Kokul Thanikasalam; methodology, Pabasara Surasinghe, and Kokul Thanikasalam; software, Pabasara Surasinghe; validation, Pabasara Surasinghe; formal analysis, Pabasara Surasinghe; investigation, Pabasara Surasinghe, and Kokul Thanikasalam; data curation, Pabasara Surasinghe; writing—original draft preparation, Pabasara Surasinghe; writing—review and editing, Kokul Thanikasalam; visualization, Pabasara Surasinghe, and Kokul Thanikasalam; supervision, Kokul Thanikasalam;

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