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RESEARCH ARTICLE

Computational Archeaology

Chronological attribution of Sinhalese inscriptions using deep learning approaches

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Abstract: A study of this caliber can be identified as a profound source for a wealth of knowledge as the aim of this study is to present chronological attribution of Sinhalese inscriptions based on deep learning approaches. Inscriptions shed light on a multitude of information such as chronicled civilizational thought, economic status, language evolution, cultural boundaries, details of royal officers, local rules, ethnic groups, land tenure, religious activities, beliefs, and trade and industries. Inscriptions are major assets to showcase inclusive of listed above, multitude information; hence, the benefits served by a study of high caliber, especially to the historical heritage research and to the heritage tourism. Several computer-aided solutions have been proposed to resolve the recognition of inscriptions in the Sri Lankan context. But this paper proposes an optimized classification. A dataset of five hundred images of original Sinhalese inscriptions dating from the 3rd century BC to the present was used to train and test the models. This study adopts four deep learning models to classify Sinhalese inscriptions: a newly proposed convolutional neural network model, and the pre-trained models Inception-v3, VGG-19, and ResNet-50. Palaeographical and morphological rules were adopted in the manual classification of Sinhalese inscriptions into a number of eras, namely, the Early Brahmi (3rd century BC to 1st century AD), Late Brahmi (2nd century AD to 4th century AD), Transitional Brahmi (5th century AD to 7th century AD), Medieval Sinhala (8th century AD to 14th century AD), and Modern Sinhala (15th century AD to the present). The results of the study indicate promising outcomes with accuracies of 70.66%, 85.94%, 57.44%, and 58.77% respectively for used four models. Further, the study revealed that the Inception-v3 model outperformed in classifying the Sinhalese inscriptions in respective eras.

Keywords: Convolutional neural network, deep learning, Sinhalese inscriptions, transfer learning.

INTRODUCTION

Inscriptions are documents which were inscribed by our ancestor on stone surfaces in ancient times. The Ministry of Cultural Heritage, Department of Archaeology and other relevant authorities in respective countries have identified the values of inscriptions and taken measures to preserve such inscriptions. A great number of ancient inscriptions have been discovered in Sri Lanka, revealing the rich history and culture of this fascinating country. According to the literature, 4000 stone inscriptions have been discovered and around 1,500 of them recorded (Bandara & Warnajith, 2012). In Sri Lanka, ancient inscriptions offer valuable insights into the donations and maintenance of temples, the construction of water tanks, and the establishment of rules for civilians. Some inscriptions can be observed under the drip ledges of caves, rocks, pillars, and slabs. Inscriptions belong to different categorizations based on eras. Deep learning approaches have shown remarkable performance in automating tasks, with the potential to achieve high accuracies in a wide range of classification and detection problems (Rustam *et al*., 2021).

Several past studies focused on recognizing inscriptions in the Sri Lankan context. Some of those studies have been conducted to recognize and digitize some Brahmi and Sinhala characters found in inscriptions, but most of those studies have failed to recognize and translate the whole content of the inscriptions and classify the inscriptions based on palaeography and morphology. At present, there is no standardized classification system for Sinhalese inscriptions. According to archaeology experts, classification of inscriptions is made based on research findings of researchers in the field (Deraniyagala, 1992).

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The aim of this study is to classify Sinhalese inscriptions both manually and computationally, based on the evolution of Sinhala characters as well as the palaeographical and morphological data of the Sinhalese inscriptions. Different deep learning models, including those with transfer learning techniques, were employed to classify the inscriptions based on the results of manual classification. The performance of the model was analyzed based on their accuracy.

There are few studies carried out related to this research. One of the research groups actualized a computational framework to set up the accurate characters of early Brahmi scripts of Sri Lankan inscriptions (Bandara, 2014). The study was carried out in four major steps. As an initial step, Brahmi scripts were converted to photographic data. Based on the photographic data Brahmi characters were identified. Then a database was created based on the identification results. An optical image scanner with the resolution of 300 pixels per inch was utilized to scan the image. Adobe Photoshop CS3 and MATLAB were used for primary image processing and further processing respectively, to identify the ideal shape of the Brahmi characters. The Majority algorithm was proposed in this research. The system showcases the accurate alphabet fonts of early Brahmi scripts of Sri Lankan inscriptions.

Yet another group created a computerized system to detect inscription characters and location of the inscription site. The system comprises two major modules: OCR and geological information system (GIS) consisting of two databases; one to support OCR which contains images and Sinhala interpretation of inscriptions and the other database to store geological information of inscriptions (Ruwanmini *et al*., 2016). In the preprocessing phase, binarization, boundary detection, segmentation and thinning are involved. After the completion of the binarization phase, Ostu's method was applied. Next, feature extraction and classification are taken into consideration. The K-mean algorithm was used for clustering.

Another study reports an approach to recognize Brahmi characters in ancient inscriptions in Sri Lanka. That system comprises an artificial neural network agent, lexical agent, structure analyst agent, and semantic agent. Various image processing techniques were employed to pre-process the image dataset. The lexical, structure analyst, and semantic agents were used to correct mistakenly identified characters. The output of the system consists of relevant Sinhala Unicode characters for the recognized Brahmi character string. This system has achieved an accuracy of 84% (Peiris, 2010).

Convolutional neural network (CNN) based classification was applied to identify similarities of modern Japanese characters and Kanji characters. The study was based on two datasets Kuzushiji-Kanji and KanjiVG. The datasets were trained using both recurrent neural network (RNN) and a mixture density network (MDN) (Heenkenda & Fernando, 2020). Initially, two separate convolutional variational autoencoders were trained on the Kuzushiji-Kanji dataset and the pixel version (64*64 pixel resolution) of the KanjiVG dataset. The datasets were compressed into their own 64 dimensional latent space z_{old} and z_{new}, and an MDN with two hidden layers was trained to model the density function, which can be represented as $P(z_{new}|z_{old})$ and approximated as a mixture of Gaussians. Finally, a Sketch-RNN model was used to generate Modern Kanji based on z_{new}.

A deep neural network-based text restoration model which recovers missing characters from a damaged text input in Greek inscriptions called PYTHIA, is the first ancient text restoration model (Assael *et al*., 2019). The dataset consists of 3.2 million words from Greek inscriptions written in the ancient Greek language dating from before the 7th century BCE to 5th century CE. The model was created based on long short term memory (LSTM). The system achieved a character error rate of the computerized system 30.1% which is significantly lower than the human recognition rate of 57.3%.

MATERIALS AND METHODS

Population and sampling technique

The population of this study consisted of a pool of inscriptions written in the Sinhala language and vetted by the subject experts in the field of archaeology. The study's inclusions consisted of images, videos, literature, text, and translations of Sinhalese inscriptions. Meanwhile inscriptions that were not accessible due to antiquities legislation, the condition of the inscription surface and environmental factors, such as height, were excluded from the study.

Convenience sampling was employed as the sampling technique for this study. Under the guidance of archeological experts and based on the density of Sri Lankan inscriptions site maps, data were collected from various districts, including Anuradhapura, Polonnaruwa, Ampara, Kurunegala, Puttalam, Vavuniya, Trincomalee, Batticaloa, Hambantota, Kandy, Kegalle, Matale, Badulla, Monaragala, Nuwara Eliya, Gampaha, and Rathnapura. Additionally, some inscriptions were obtained from the archeological museum in Colombo and included in the study.

Data Collection

Data collection methods

The research utilized a range of data gathering techniques including interviews, field visits, observation, archeological scholarly books, and websites. In-depth interviews, both informal face-to-face and telephone, were conducted with archeological experts and museologists to capture valuable insights and perspectives. The knowledge and perceptions of these subject experts greatly enriched the research and ensured its quality. Qualitative data was primarily gathered through interviews with archeological specialists, including in-depth discussions with site officers and knowledge experts. Face-to-face interviews and online meetings were conducted with site officers at inscription sites and academic staff members to obtain comprehensive information. The data collection process utilized a variety of devices, platforms, and tools to facilitate this, including:

- Data collection sheets: Microsoft Word, Microsoft Excel, Text Analyzer
- To get photographs and videos: Android mobile phone
- Interview protocols: Semi-structured
- Recording methods: Voice recording, taking notes, taking images and videos of inscriptions

The following qualitative data were gathered:

- Images, photographs, and videos of inscriptions which were written in Sinhala language
- Archeological terms
- Paleographical and morphological data for the Sinhala language
- Translated text of inscriptions
- Sinhala language evolution related to inscriptions

The Department of Archaeology maintains a collection of inscriptions' estampages. However, for this study, the focus was on onsite images as the majority of the estampages in the collection were captured many decades ago.

Manual classification of Sinhalese inscriptions

Prior to applying machine learning approaches, the data was analyzed manually using a thematic analysis approach. Specifically, content analysis was utilized as a manual qualitative data analysis technique, given the historical nature of the data and the importance of cultural, social, and economical preservation, identifying patterns in the written text, including inscriptions, archaeological terms, and palaeographical and morphological data for the Sinhala language, as well as the evolution of the Sinhala language over time.

Thematic analysis

Sinhalese inscriptions have been categorized into different eras by researchers based on their convenience, rather than adhering to a proper set of standards. To simplify and standardize the ideas presented within the inscriptions, a thematic analysis was carried out. Additionally, voice cuts and recordings of subject experts in the field of archaeology were transcribed to identify patterns which make arguments, ultimately leading to a better understanding of the study through examination of differing expert opinions. However, it was a challenging task to compose different ideas into a coherent whole.

To ensure the accuracy of the analysis, thorough examinations were carried out with scholarly articles that were gathered to identify translations of the text on inscriptions and to classify the inscriptions themselves.

Computational classification for Sinhalese inscriptions

This section illustrates the different machine learning techniques which were used to classify Sinhalese inscriptions. CNNs became a state-of-the-art method for classification of images (Rustam *et al*., 2021). As images of inscriptions are limited, transfer learning techniques were used for this research. In this section, we describe different deep CNN models used in this research.

Dataset

The dataset comprises images obtained from the original Sinhalese inscriptions, and the number of relevant estampages of the inscriptions can be found from the Department of Archaeology and Central Cultural Fund. To increase the number of images and enhance the dataset's variability, data augmentation techniques were utilized on the original dataset. Augmentation methods such as translation, rotation, scale, and zooming were applied. Following the application of these augmenting methods, the total number of images in the dataset increased to 475 as shown in Table 1.

Table 1: Number of original Sinhalese inscriptions and number of augmented images in the dataset

Category	No of original Sinhalese inscriptions	No of augmented images
Early Brahmi	16	110
Late Brahmi	10	90
Transitional Brahmi	7	72
Medieval Sinhala	15	100
Modern Sinhala	14	103

Classification models

Figure 1 shows the classification approach of Sinhalese inscription.

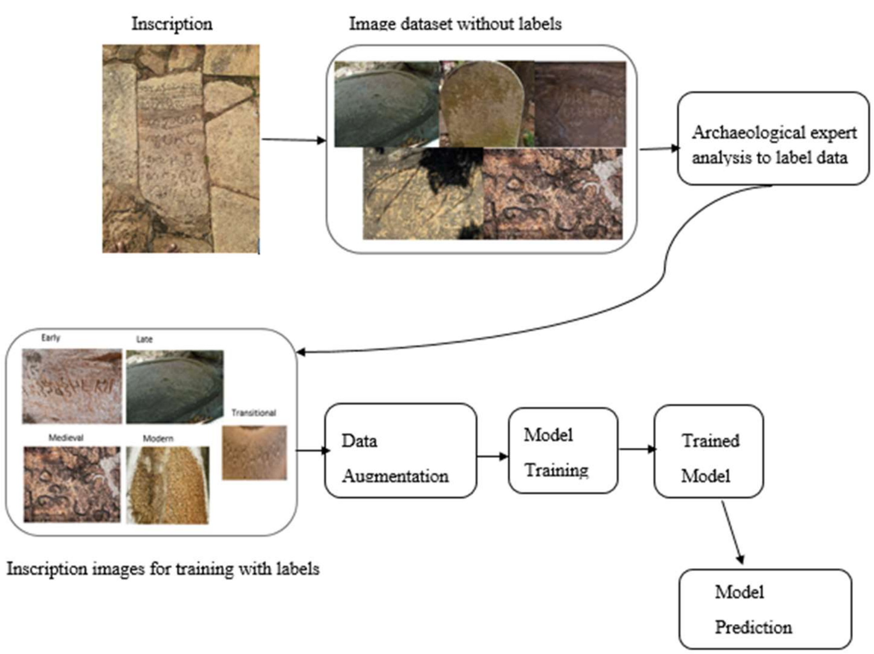

Figure 1: Classification approach of Sinhalese inscriptions

CNN model trained from the scratch

CNN is a widely used and powerful type of neural network that is particularly effective at processing complex computational data. The CNN model developed from scratch consists of seven convolutional layers, pooling layers, flattening layers, non-linear activation layer and dropout layer. The primary convolutional layer is responsible for extracting feature maps from input images, while the max pooling layer is utilized to identify sharp features within the proposed system. The activation function employed in this CNN model is the ReLU (rectified linear unit) function. Figure 2 shows the architecture of CNN model trained from the scratch.

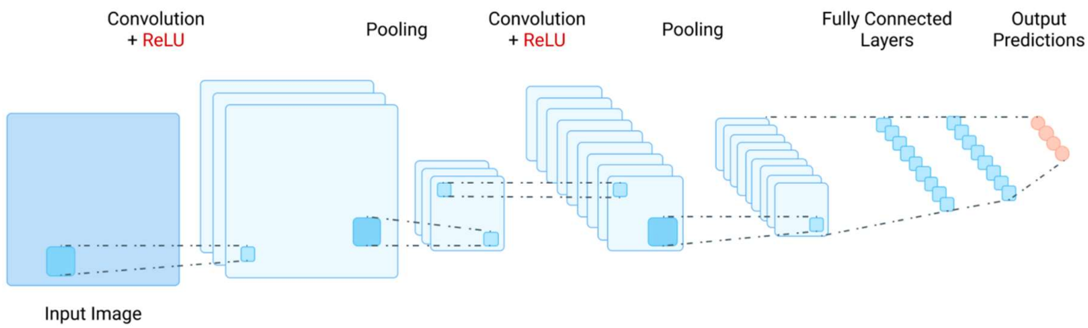

Figure 2: Architecture of CNN model developed from scratch

Inception-v3

Inception-v3 is a convolutional neural network (CNN) that builds upon the GoogLeNet (Szegedy *et al*., 2015). It is pre-trained and utilizes transfer learning for feature extraction. This approach reduces computational complexity by decreasing the number of parameters that need to be trained. The system's high-level architecture is illustrated in Figure 3.

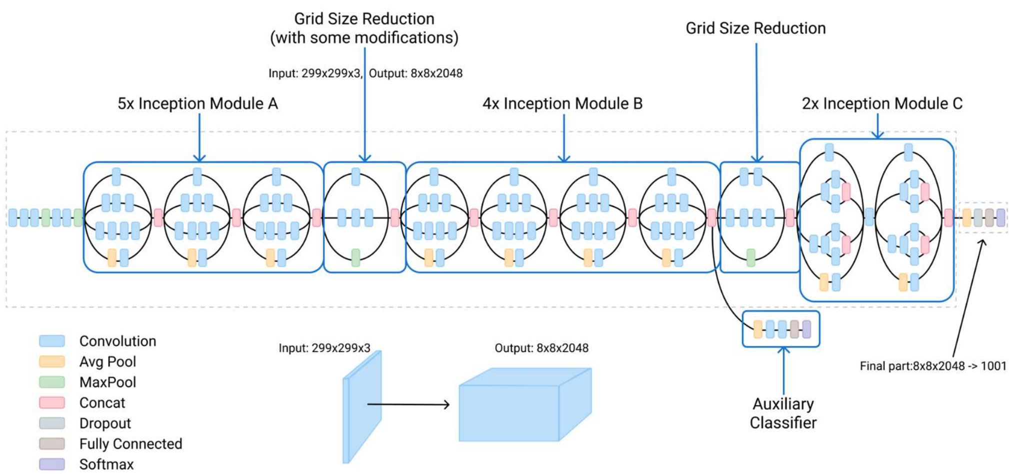

Figure 3: The high level architecture of Inception-v3 (https://cloud.google.com/tpu/docs/inception-v3-advanced)

VGG-19

The VGG-19 model, as depicted in Figure 4, is composed of six structures that incorporate multiple connected convolutional layers and fully connected layers. The convolutional kernel is fixed at 3 x 3, while the input size is 224 x 224 x 3. The model performs feature extraction on its own, and it utilizes max-pooling for down-sampling, with the rectified linear unit (ReLU) serving as the activation function. The down-sampling layer plays a crucial role in improving the model's anti-distortion ability, while simultaneously reducing the number of parameters, as stated by Jian Xiao *et al*. (2020).

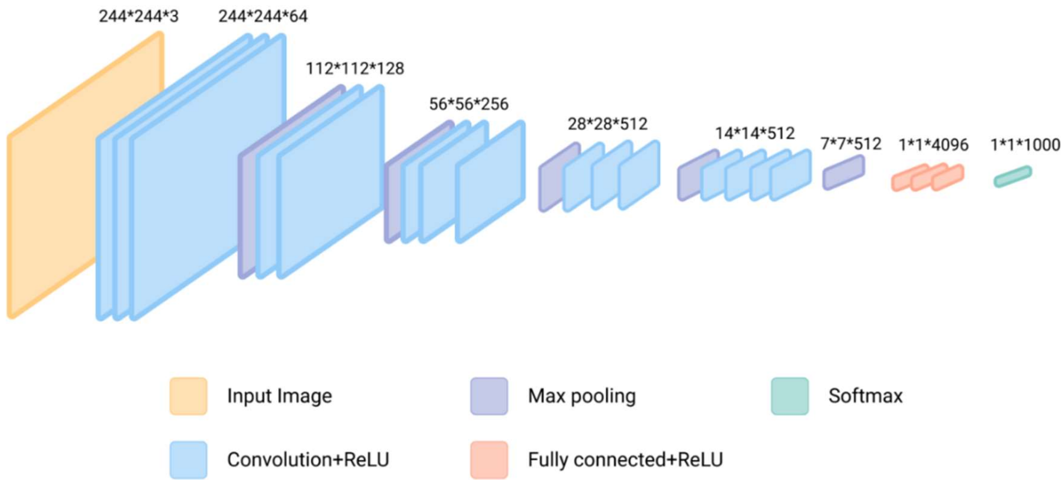

Figure 4: The high level architecture of VGG-19 model (Jian Xiao *et al*., 2020)

Resnet-50

The ResNet-50 model, illustrated in Figure 5, is a deep residual network that consists of 50 layers with a significant depth (Kaiming *et al*., 2016). By maintaining the same number of filters for the same feature map size, the model reduces the time complexity associated with training deep networks. ResNet-50 is an extension of ResNet-34 and builds upon its architecture to further enhance the model's performance.

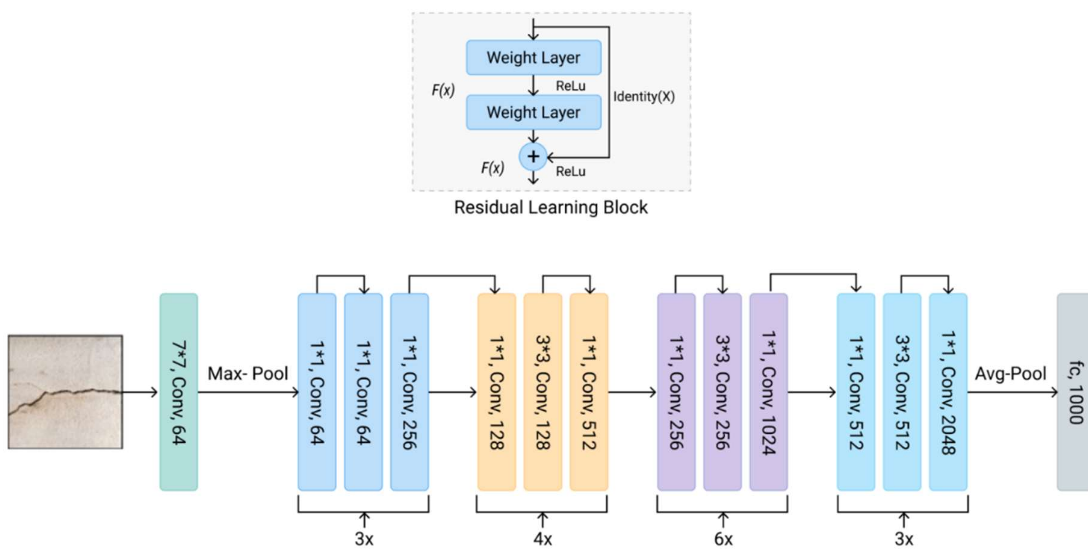

Figure 5: The high level architecture of ResNet-50 model (Ali *et al*., 2021)

RESULTS AND DISCUSSION

Results of manual classification of Sinhalese inscriptions

Palaeography of Sinhalese inscriptions

The Sinhala characters originated from the Brahmi characters, with their evolution beginning around 1 BC (Thennakoon, 1957). Over time, the shapes of the Sinhala letters began to diverge from those of the Brahmi characters, becoming more circular or rounded. Most of the inscriptions in Sinhalese were written from left to right, although some were written from right to left on rare occasions. During the 8th century, Sinhala characters were influenced by Pallava characters (Thennakoon, 1957).

Some of the Sinhala characters, such as අ, උ, ක, ග, ච, ජ, ඩ, න, බ, ය, ර, ල, ව, හ, and ළ, were derived from Brahmi letters, while others such as ඉ, ඔ, ධ, ඡ, ණ, ථ, ඵ, හ, ෂ, and ශ were derived from Pallava letters. By the 16th century, the Sinhala letters had become more rounded, as they appear today. However, the evolution of these characters came to an end due to the advent of printing technology.

Pictorial symbols

A number of inscriptions contain pictorial symbols that are not Sinhala characters. These symbols may appear at the beginning or end of a line of Sinhala characters, or above or below them. In some inscriptions known as ‘Aththani’ inscriptions, which were created when donating to temples and hospitals, symbols such as a dog, crow, and monk's fan were common. These symbols served to emphasize that anyone who misused public property would be reborn as a dog or crow in their next life. In inscriptions from the 15th century onwards, common symbols include Bo leaves and Dharmachakra.

Phonology of Sinhalese inscriptions

The inscriptions denote details of pronunciation and phonetic modifications. Spoken Sinhala consists of 40 segmental phonemes, comprising 14 vowels and 26 consonants, which includes a unique set of 4 prenasalized voiced stops. In contrast, the modern Sinhala character set comprises 20 vowels and 40 consonants. However, for this research, these phonemes were not deeply considered.

Morphology of Sinhalese inscriptions

The Sinhalese language of the past typically ended in a vowel, and it was rare to find pronominal forms in the written scripts of that time. Nouns were composed of a base word and an ending, which could be simple, derived, or complex. Sinhalese inscriptions included a set of morphophonemic rules known as ‘Sandi’.

Categorization of Sinhalese inscriptions

At present, there is no standard method for categorizing Sinhalese inscriptions into distinct historical eras. Various arguments exist within the academic community, and researchers have developed different classifications for their individual studies. However, due to the historical nature of the inscriptions, it is not always practical to pinpoint their precise time period. Nonetheless, experts in the field of archaeology have introduced several classifications that have greatly advanced our understanding of these important historical artifacts.

Lankage categorized the inscriptions into five eras as follows (Lankage, 1996).

- 1st era -: 3 Century BC - 1 Century BC
- 2nd era -: 1 Century AD - 3 Century AD
- 3rd era -: 4 Century AD - 5 Century AD
- 4th era -: 6 Century AD - 7 Century AD
- 5th era -: 8 Century AD - 10 Century AD

Another categorization based on the palaeography of inscriptions was revealed in Salapathalamaluwa (Mudiyanse, 2020).

- 1st era -: 2 Century BC - 1 Century BC
- 2nd era -: 1 Century AD - 3 Century AD
- 3rd era -: 3 Century AD - 5 Century AD
- 4th era -: 5 Century AD - 8 Century AD
- 5th era -: 8 Century AD - 10 Century AD
- 6th era -: 10 Century AD - 12 Century AD

Thennakoon mentioned eight eras in the book "Parani Lankawa ha Shilalipi," which considered inscriptions up to Kandy era as follows (Thennakoon, 1957).

- 1st era -: 3 Century BC - 1 Century AD
- 2nd era -: 1 Century AD - 5 Century AD
- 3rd era -: 5 Century AD - 8 Century AD
- 4th era -: 8 Century AD - 11 Century AD
- 5th era -: 11 Century AD - 13 Century AD
- 6th era -: 13 Century AD - 15 Century AD
- 7th era -: 15 Century AD - 16 Century AD
- 8th era -: 16 Century AD - 19 Century AD

Karunarathne discussed seven eras in the book 'Sinhala Shila Lekhana,' which considered inscriptions up to the year 1815 (Karunarathne, 1956).

- 1st era -: 300 BC - 1 BC
- 2nd era -: 1 AD - 300 AD
- 3rd era -: 300 AD - 800 AD
- 4th era -: 800 AD - 1000 AD
- 5th era -: 1000 AD - 1200 AD
- 6th era -: 1200 AD - 1415 AD
- 7th era -: 1415 AD - 1815 AD

Fernando defined two eras based on palaeography data as follows (Deraniyagala, 1992).

- Brahmi era -: 3 Century BC - 7 Century AD
- Sinhala era -: 7 Century AD - 15 Century AD

However, based on the evolution of Sinhala characters, inscriptions are categorized commonly into five eras for documentation and academic purposes, as follows.

- Early Brahmi -: 3 Century BC - 1 Century AD
- Late Brahmi -: 2 Century AD - 4 Century AD
- Transitional Brahmi -: 5 Century AD - 7 Century AD
- Medieval Sinhala -: 8 Century AD - 14 Century AD
- Modern Sinhala -: 15 Century AD - Present

The categorization outlined above was duly considered during the process of computational classification in this research.

Results of classification models

The classification models were implemented using the Tesla K80 GPU processor, which boasts a RAM size of 12.6 GB. Our dataset consisted of 475 images, which were divided into training and validation sets at ratios of 85% and 15%, respectively. During the training phase, we utilized the categorical cross entropy function as the loss function, as it is optimal for multi-class classification tasks. We trained the CNN models (including Inception-v3, VGG-19, and ResNet-50) by varying parameters such as filter size and the number of layers for each model. Additionally, we employed transfer learning techniques. Our batch size was set at 32 and we trained each model for 100 epochs. Finally, we evaluated the classification models using accuracy.

CNN model trained from the scratch

The model achieved accuracies of 92.01% and 74.12% for the training and validation datasets, respectively.

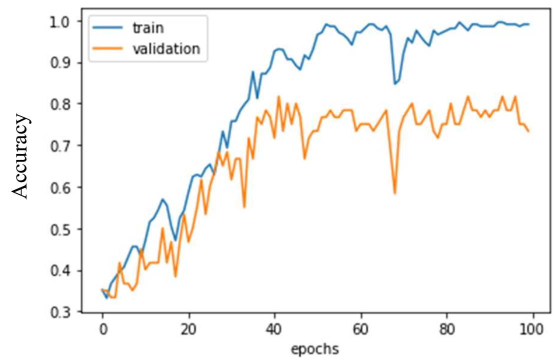

Figure 6: Training and validation accuracies of CNN model

Inception-v3

The model obtained accuracies of 93.25% and 87.21% for the training and validation datasets, respectively.

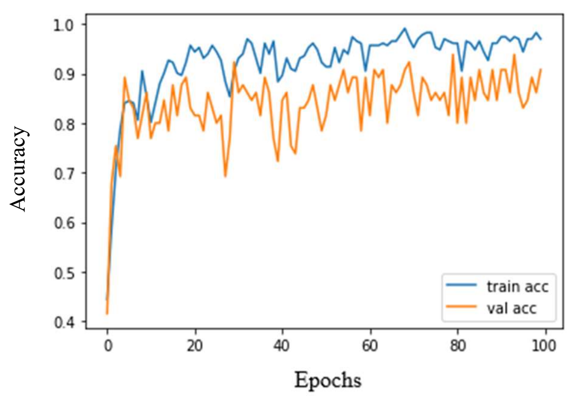

Figure 7: Training and validation accuracies of Inception-v3

VGG-19

The model achieved accuracies of 91.01% and 58.33% for the training and validation datasets, respectively.

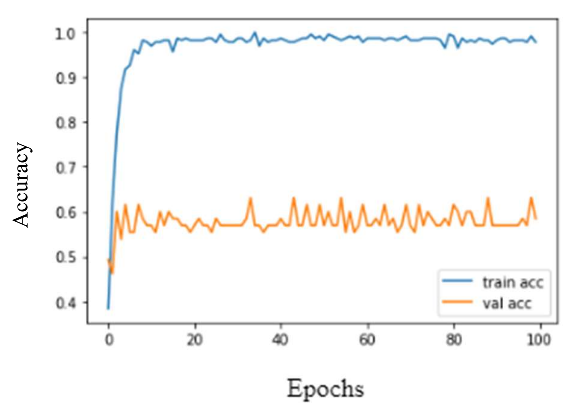

Figure 8: Training and validation accuracies of VGG-19

Resnet-50

The model achieved 78% and 58.74% accuracies for training and validation datasets respectively.

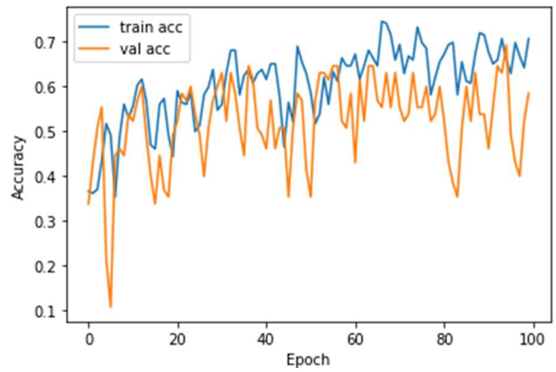

Figure 9: Training and validation accuracies of ResNet-50

Models - Comparison and analysis

Table 2: Results of classification models

Model	Evaluation parameter	Score
CNN model trained from scratch	Training accuracy	92.01%
	Validation accuracy	74.12%
Inception-V3	Training accuracy	93.25%
	Validation accuracy	87.21%
VGG-19	Training accuracy	91.01%
	Validation accuracy	58.33%
ResNet-50	Training accuracy	78.00%
	Validation accuracy	58.74%

Cross-validation was employed to validate the effectiveness of the models, using K-fold cross-validation. The dataset was initially shuffled and divided into K groups. For each group, the following steps were followed: the group was held out, the remaining data was used as the training dataset, a model was trained on the training dataset, and the model was evaluated on the validation dataset.

Table 3: Models performances with 10-fold cross validation

Iteration	CNN model trained from scratch	Inception-V3	VGG-19	ResNet-50
Iteration 1	70.01%	85.27%	55.75%	57.42%
Iteration 2	71.30%	86.21%	58.10%	60.10%
Iteration 3	71.21%	87.01%	57.51%	59.30%
Iteration 4	70.03%	84.99%	58.01%	64.20%
Iteration 5	71.01%	87.21%	56.62%	56.59%
Iteration 6	70.12%	85.66%	56.61%	58.32%
Iteration 7	70.33%	85.38%	58.02%	57.99%
Iteration 8	72.54%	85.68%	57.45%	57.85%
Iteration 9	70.31%	84.69%	58.11%	57.99%
Iteration 10	69.81%	87.31%	58.25%	57.99%
Average	70.66%	85.94%	57.44%	58.77%

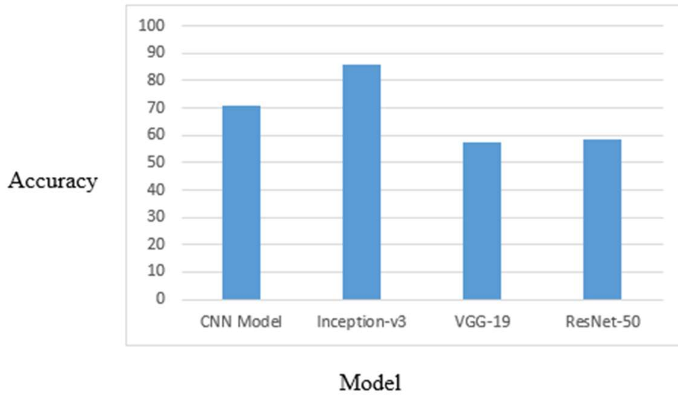

Figure 10: Models' average accuracy score comparison with 10-fold cross validation

This study was conducted in four main steps: data collection, manual classification of Sinhalese inscriptions, computational classification of Sinhalese inscriptions, and analysis of the results. The computational classification process relied on the manual classification carried out previously and was carried out subsequently. The accuracy of the manual classification was verified by collaborating with experts in archaeology.

To document and study Sinhala character inscriptions, paleographical and morphological data have been used to categorize them into five eras: Early Brahmi, Late Brahmi, Transitional Brahmi, Medieval Sinhala, and Modern Sinhala. This classification system was taken into account for the computational classification in this research, which covered twelve districts in Sri Lanka based on the density of inscriptions. Four models were tested for classifying Sinhalese inscriptions, with the first model using only convolutional neural networks and not being a pre-trained model, while the other models utilized transfer learning techniques. Out of these models, the Inception-v3 model achieved the highest accuracy.

Only a few studies have been conducted to identify specific characters in Sinhalese inscriptions within the Sri Lankan context, and there is currently a lack of computational approaches for classifying Sinhalese inscriptions from different eras. However, the application of four deep learning models has shown promising results in the classification of Sinhalese inscriptions.

CONCLUSION

To date, no significant computational study has been conducted to classify Sinhalese inscriptions from different eras, highlighting a gap in the field of computational archaeology. This study aims to address this issue by utilizing a dataset consisting of 475 images from 62 Sinhalese inscriptions, with data augmentation techniques employed to increase the number and variation of the samples. The findings indicate that the Inception-v3 model can accurately identify the period of Sinhalese inscriptions, achieving an 85.94% accuracy level on the validation dataset. To improve the robustness of the model, data augmentation methods can be further utilized. Moreover, the results of the study suggest that deep learning models utilizing transfer learning techniques outperform other models on this dataset.

Future Work

The authors aim to explore the use of alternative machine learning techniques for the classification of Sinhalese inscriptions and analyze their performance. Additionally, a system will be proposed to translate Sinhalese inscriptions into the English language.

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