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# Khmer Handwritten Digits Recognition using Convolution Neural Networks

Ly Sreypov[1]

[1]Information Technology and Engineering Royal University of Phnom Penh Phnom Penh, Cambodia

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**Abstract - This study focuses on developing a Convolutional Neural Network (CNN) model to recognize and classify handwritten Khmer numbers from a dataset of 19,530 images. The research addresses the challenge of duplicated number recognition by leveraging CNNs, which are highly effective for image recognition tasks in computer vision. The dataset is preprocessed, cleaned, scaled, and split into training, validation, and testing sets. Using libraries such as NumPy, Pandas, TensorFlow, Keras, and Scikit-learn, a CNN model is constructed, trained, and evaluated, achieving a 95% accuracy in predicting handwritten Khmer numbers from 0 to 9. The work highlights the efficiency and robustness of CNNs compared to other networks for this task, contributing to improved handwritten number recognition.**

***Keywords:*** *Machine Learning, Handwritten Digits Recognition, Convolution Neural Network (CNN).*

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## I. INTRODUCTION

Number handwriting is an old task but is still being studied because every country has different handwriting styles. The Cambodian script in question is the Khmer numbers. The Khmer numbers are written by adding a number from 1 to 9 and/or a number to the power of ten from 10 to 1,000,000. The classification of Khmer numbers is due to the many available forms that can be generated from 1 to 6 strokes. Each shape does not change from existing to the power of ten, just the number changes. The experiment will generate images from one to nine strokes. The best available form is the image of the stroke that is not changed, and the number of strokes is one. We generated a total of 45,153 images for numbers from 0 to 9 and used 40,583 images, randomly choosing 90% of them as a training dataset.

The background of a lot of research is to generate shapes for various defined purposes or for document analysis. This handwriting is focused only on Khmer numbers, so the test results cannot be compared with other handwriting tests. In the past, character recognition has been performed in many complex architectures for both English and non-English characters. The most common deep learning technique in the area of Khmer scripts, which consist of Khmer numbers embedded in literature, has been developed, and the number of Khmer number handwriting studies is increasing but still growing. The existing model is Deep Multimodal Fusion and CNN Model with Small Sample. The model consists of a convolutional neural network with random initialization.

Study is focused on Khmer ten number such as 0, ១, ២, ៣, ៤, ៥, ៦, ៧, ៨, ៩. The dataset has 19530 images for train (13470), validation (3960) and test (2100).

## II. RELATE WORK

Sarayut Gonwirat and Olarik Surinta investigated deep Convolutional Neural Networks (CNNs) for recognizing Thai handwritten characters using the THIC68 dataset. Their study compared training from scratch versus transfer learning with VGGNet-19 and Inception-ResNet-v2 architectures. Results demonstrated that VGGNet-19 with transfer learning not only reduced training time but also achieved a high recognition accuracy of 99.20% through 10-fold cross-validation, highlighting its effectiveness for Thai handwriting recognition tasks. [1]

Bayram Annaurov and Norliza Mohd Noor explored the use of Convolutional Neural Networks (CNNs) for recognizing Khmer handwritten symbols, aiming to digitize large Khmer document corpora. The dataset comprised six handwriting sets, each with 33 consonants and 17 vowels, forming 561 syllables. An ensemble of 33 CNNs, each

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trained to recognize a specific root radical, was developed for offline recognition. This CNN-based model outperformed artificial neural network (ANN) classifiers, both with full features and with dimensionality reduction, achieving a recognition accuracy of 94.85% for the Khmer alpha-syllabary system. [2]

Xuchen Song, Xue Gao, Yanfang Ding, and Zhixin Wang developed a method for handwritten Chinese character recognition by leveraging dataset expansion and Convolutional Neural Networks (CNNs). The proposed CNN topology was combined with data augmentation techniques, such as random elastic deformation, shear transformation, and small-range rotation, to enrich the training dataset. Testing on the HCL2000 Chinese character handwriting database, their approach achieved a significant reduction in error rate by 35.01%, validating the effectiveness of the proposed method for improving recognition performance. [3]

## III. DATA WORKFLOWS

Total image of dataset after processing we get 19530 images. Spilt dataset into training 13470 images and validation 3960 images.

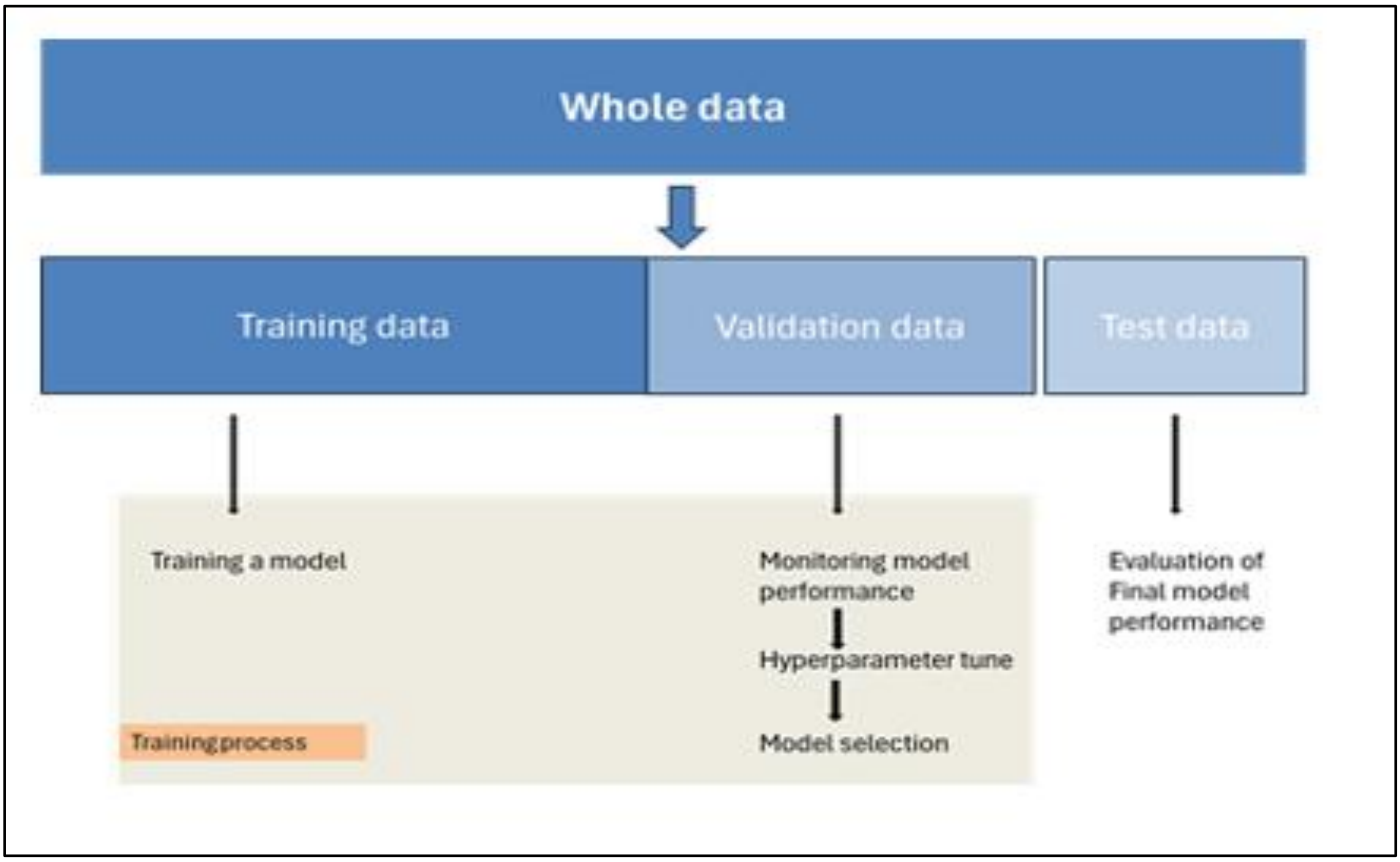


Fig 1 Data splitting and model training process

Figure 1 The whole dataset is divided into training, validation, and test sets. The training process involves training a model on the training data, using validation data for performance monitoring, hyperparameter tuning, and model selection. The test data is reserved for final model evaluation.

The processing of train and validation dataset: Resizes images to 64x64 pixels, Inverts the images colors using ImageOps.invert(black become white and viceversa) and Applies rotations to the image (from 0 to 29 degrees in steps of 1 degree) and saves each rotated version.

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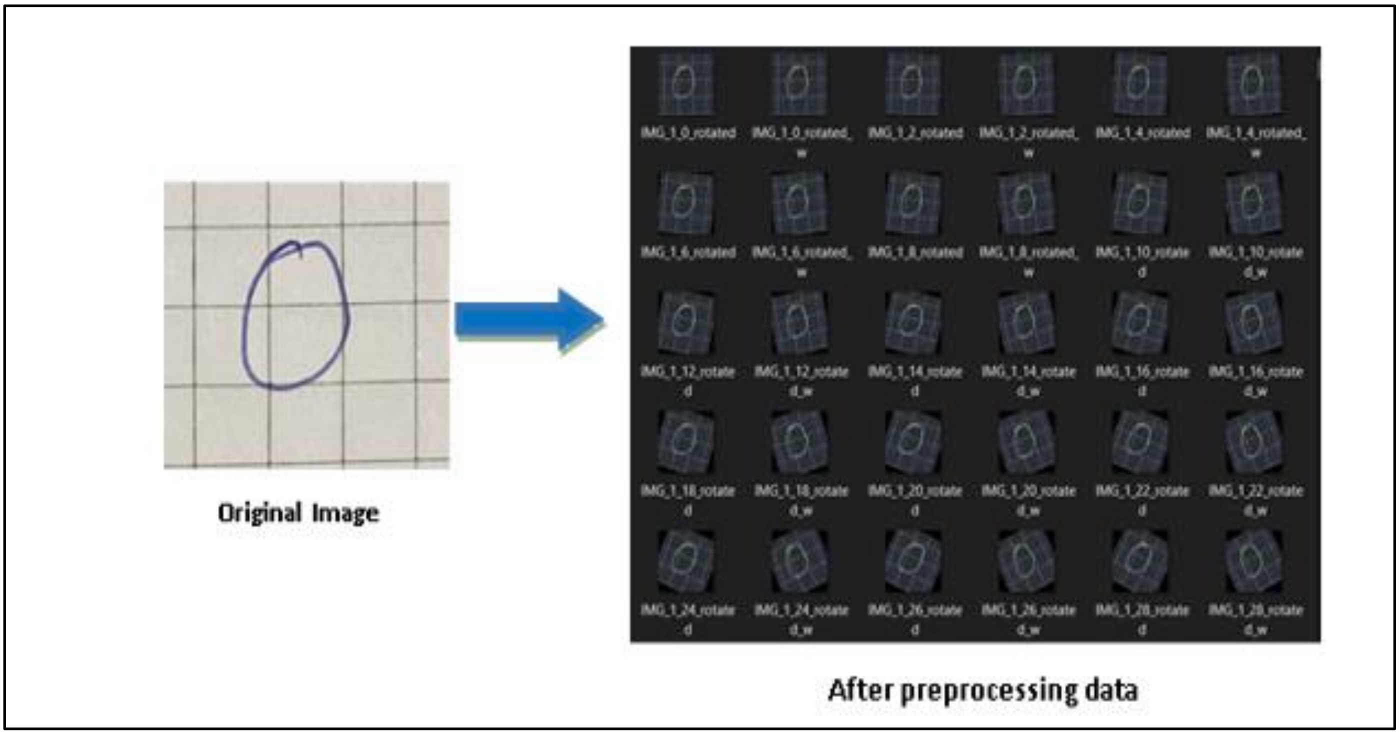


Fig 2 Process of Train and Validation

## IV. MODEL CREATION

Description of each layer in the CNN model, along with a conceptual block diagram representation.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 16, 16, 8) | 80 |
| batch_normalization (BatchNormalization) | (None, 16, 16, 8) | 32 |
| max_pooling2d (MaxPooling2D) | (None, 8, 8, 8) | 0 |
| dropout (Dropout) | (None, 8, 8, 8) | 0 |
| conv2d_1 (Conv2D) | (None, 8, 8, 16) | 1,168 |
| batch_normalization_1 (BatchNormalization) | (None, 8, 8, 16) | 64 |
| max_pooling2d_1 (MaxPooling2D) | (None, 4, 4, 16) | 0 |
| dropout_1 (Dropout) | (None, 4, 4, 16) | 0 |
| flatten (Flatten) | (None, 256) | 0 |
| dense (Dense) | (None, 64) | 16,448 |
| dropout_2 (Dropout) | (None, 64) | 0 |
| dense_1 (Dense) | (None, 10) | 650 |

Fig3 Summary Model Create

The preprocessing stage involves preparing the image data for training and validation.

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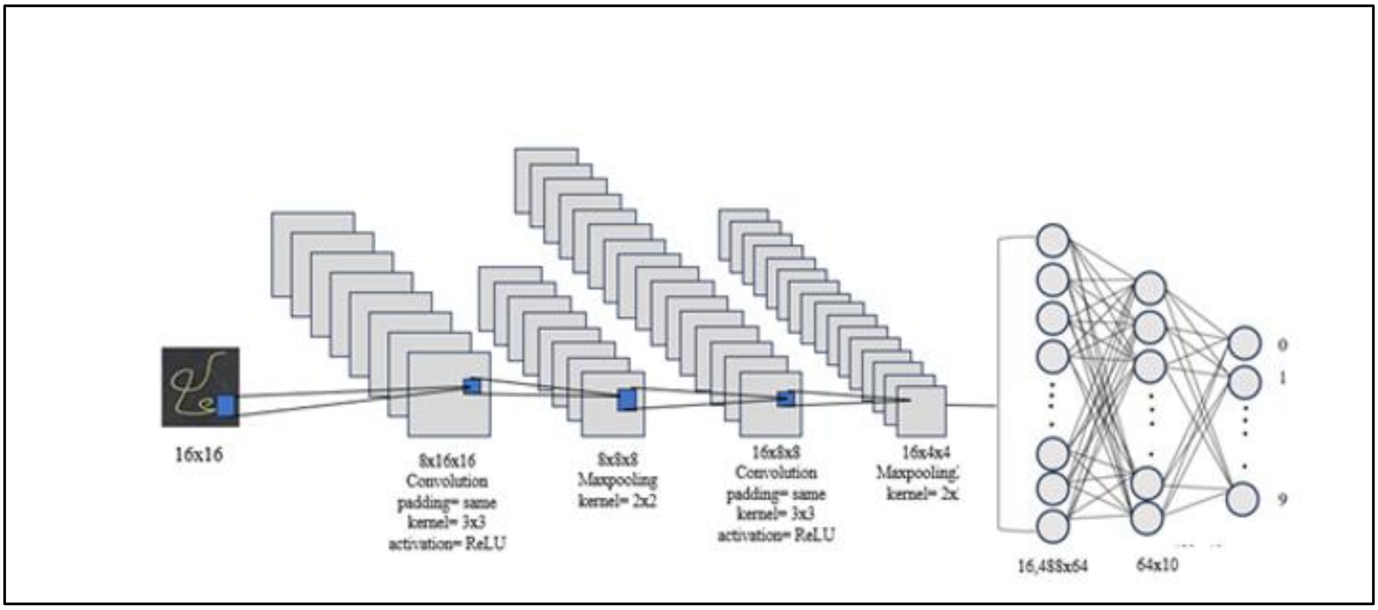


Fig 4 CNNs Block Diagram

## V. RESULTS

Final result of training and validation model. Result of training accuracy 0.9529 training loss 0.2716 validation accuracy 0.9510 and validation loss 0.2763.

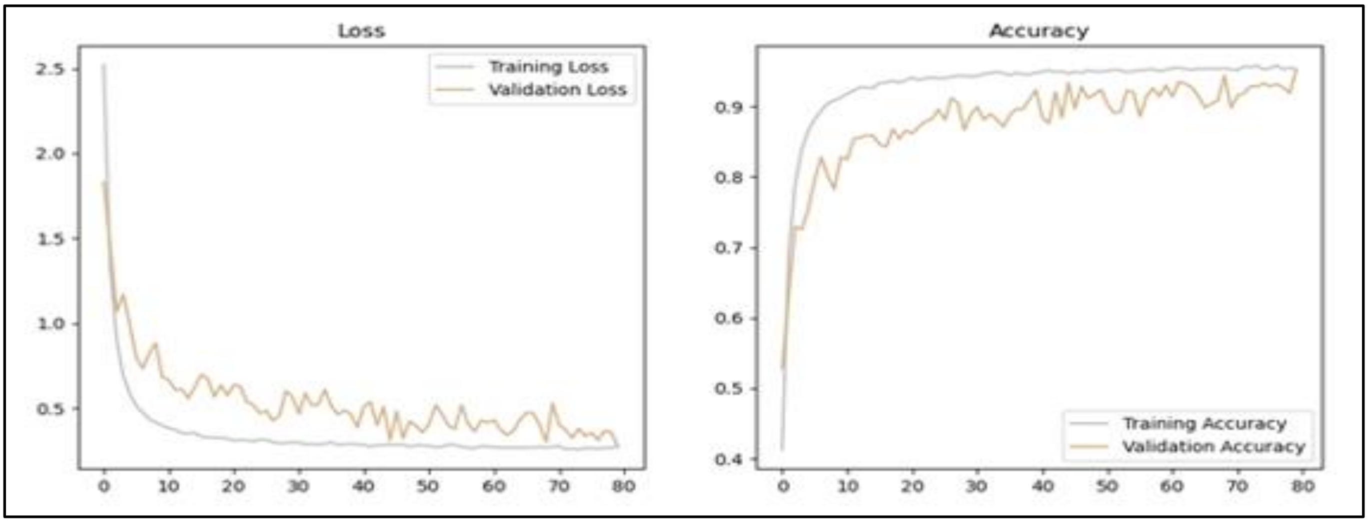


Fig 5 Accuracy

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Fig 6 Confusion Matrix of Model Predictions

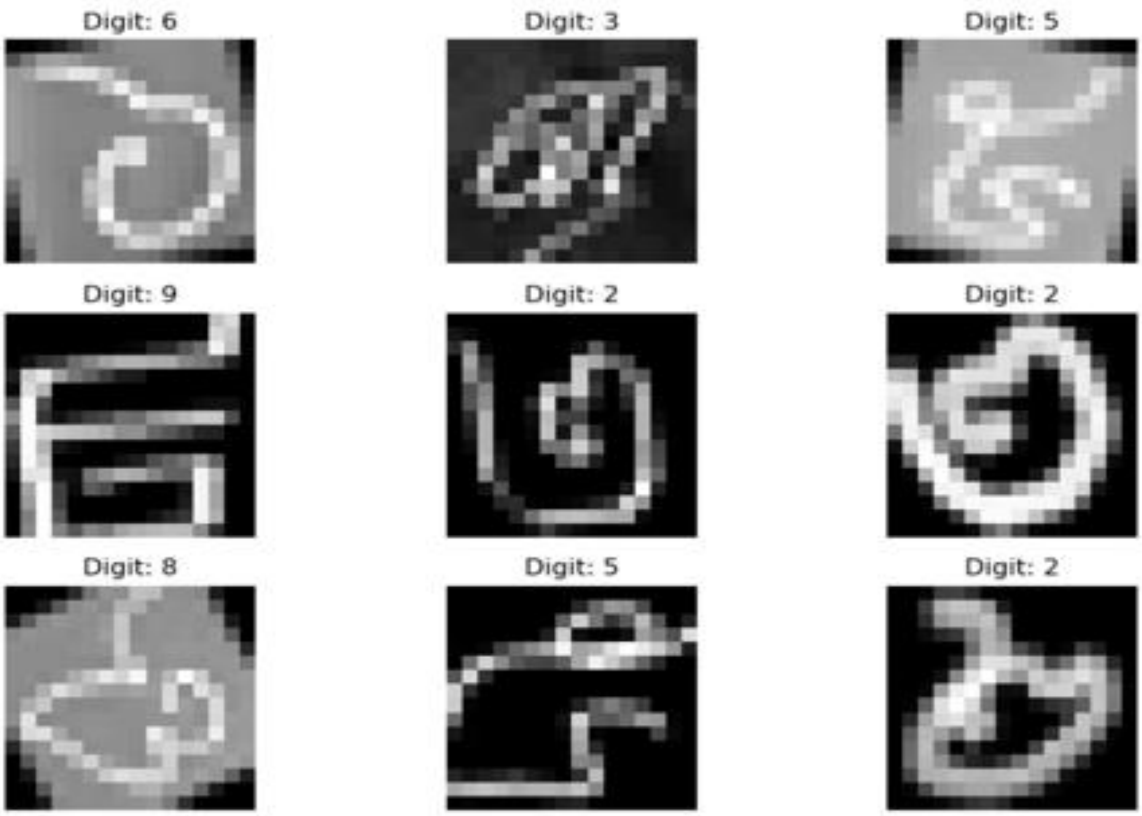


Fig 7 Result of Predicted

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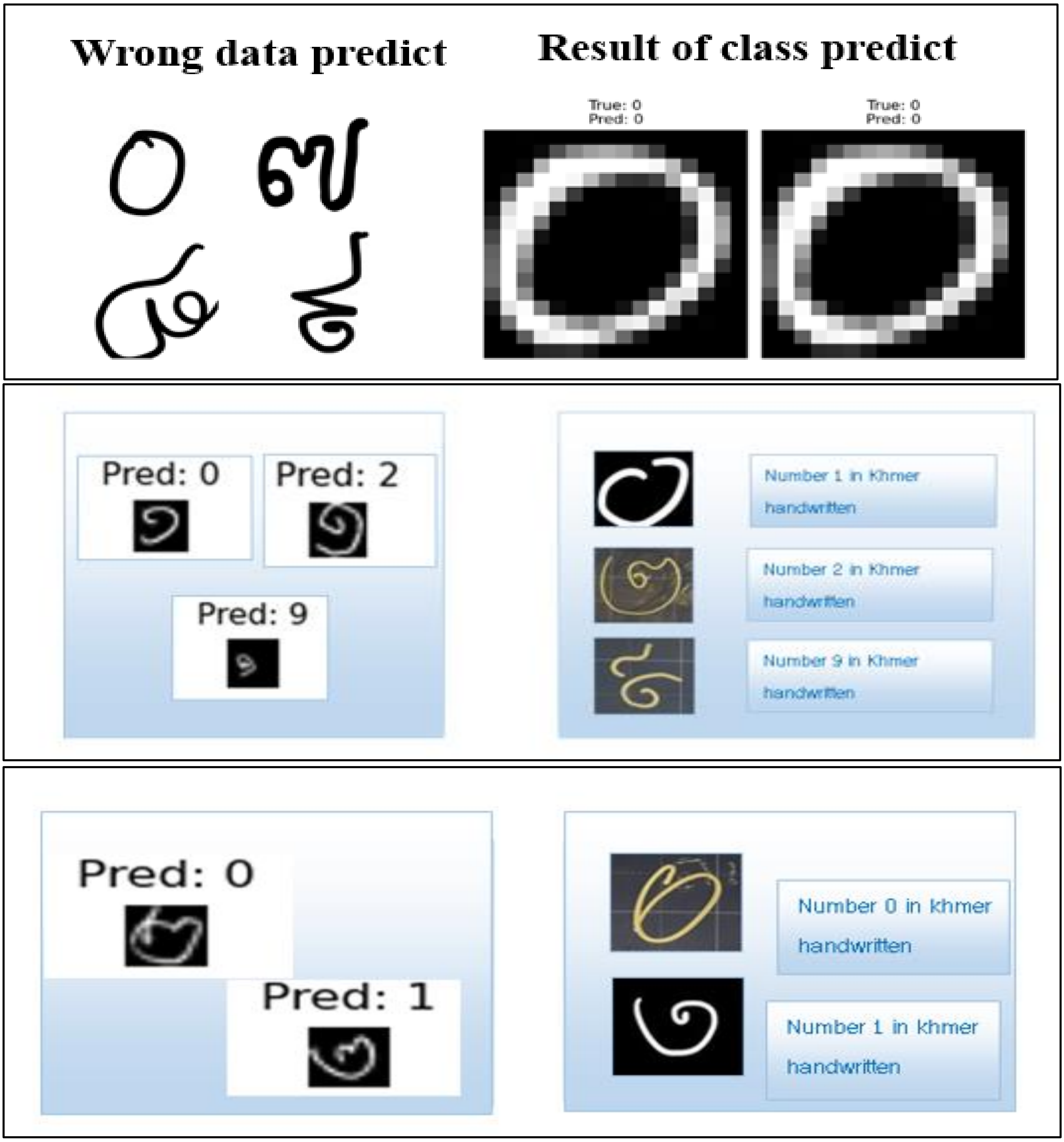
Discussion result of training and validation. Class 0, class 7, class 8, class 9 after training using this model achieved 100% accuracy because writing Khmer numbers 0,7,8,9 is different from other Khmer numbers. Class 1 after training using this model achieved 96.89% accuracy because each person's writing style is unique, resulting in similar numbers to other people. Class 2 after training using this model achieved 93.62% accuracy because each person's writing style is unique, resulting in similar numbers to other people. Class 3 after training using this model achieved 94.17% accuracy because each person's writing style is unique, resulting in similar numbers to other people. Class 4 after training using this model achieved 92.22% accuracy because each person's writing style is unique, resulting in similar numbers to other people. Class 5 after training using this model achieved 74.67% accuracy because each person's writing style is unique, resulting in similar numbers to other people. Class 6 after training using this model achieved 99.17% accuracy because each person's writing style is unique, resulting in similar numbers to other people.



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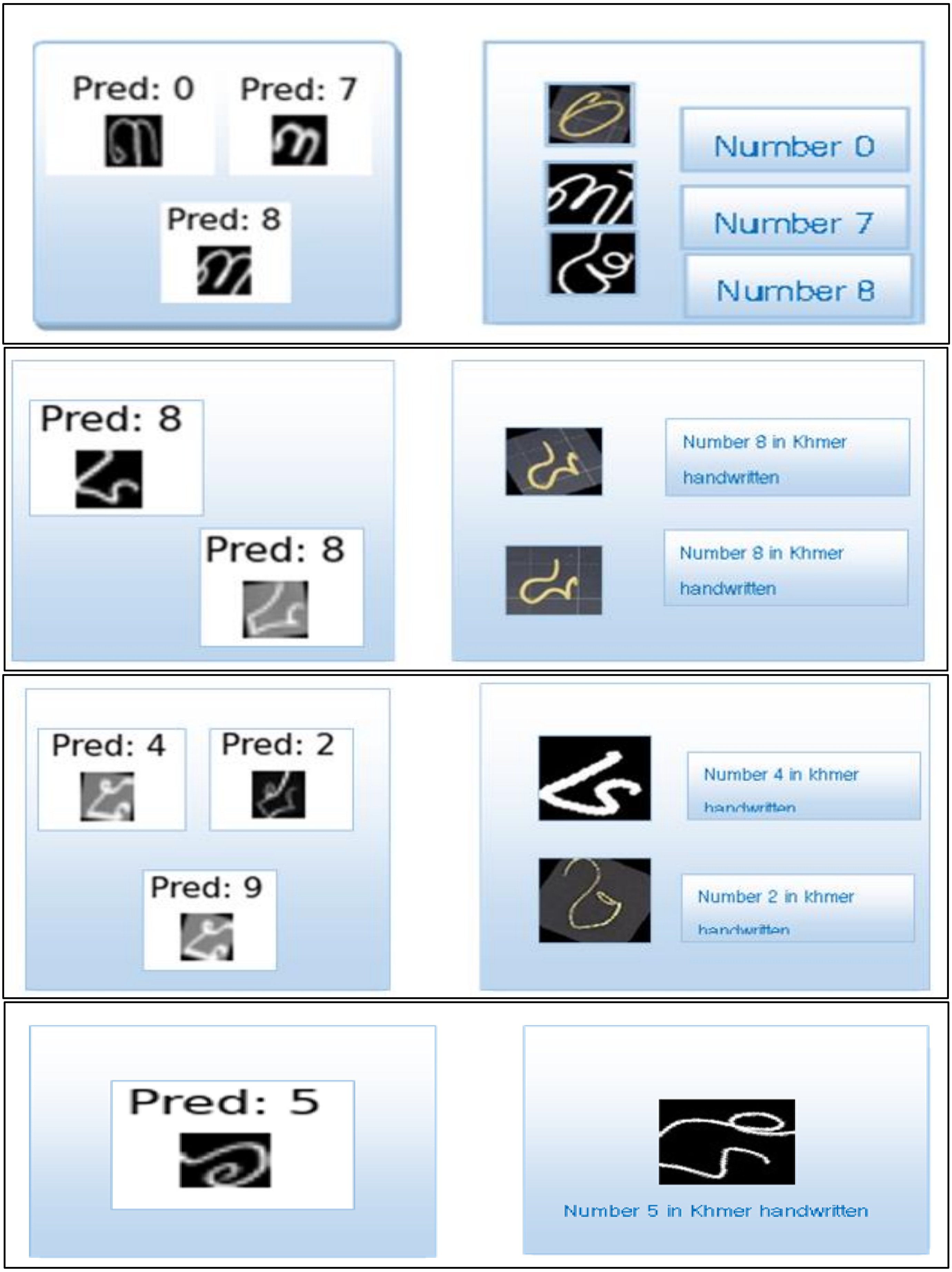


Fig 8 Wrong Data Predict and Result of Class Predict

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## VI. CONCLUSION

In this exploration of Convolutional Neural Networks (CNNs), we highlighted their significance in image recognition tasks, specifically for predicting Khmer handwritten digits (0–9). The dataset, comprising 19,530 images, was split into 69% (13,470 images) for training, 20% (3,960 images) for validation, and 11% (2,100 images) for testing. The data was preprocessed through cleaning, scaling, inversion, rotation, and shaping to ensure quality input. Using TensorFlow, a CNN model was developed, trained on the training dataset, and achieved a 95% accuracy in predicting digits 0–9 on the test set, successfully recognizing all digits.

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