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Enhanced Handwritten kannada Numeral Recognition with Deep Convolutional Neural Networks and Transfer Learning.

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ABSTRACT

In recent years, researchers have been working on developing computer programs that can recognize handwritten numbers. This is important because people write numbers in different ways, which makes it hard for computers to understand. However, not much research has been done on recognizing handwritten Kannada numbers using deep learning techniques, especially compared to other languages in India. Additionally, there aren't many publicly available datasets of Kannada numbers for computers to learn from. One way to teach computers to recognize Kannada numbers is to use transfer learning, which is starting with a model that has previously undergone training and adjusting it to recognize Kannada numbers. However, it's not clear how much the pre-trained model should be fine-tuned for best results.

One approach to teaching computers how to recognize Kannada numbers is through transfer learning. This involves utilizing a pretrained model as a starting point and fine-tuning it specifically for the recognition of Kannada numbers. However, the optimal level of finetuning required for achieving the best results remains unclear.

KEYWORDS: Convolutional neural networks, Kannada numerals, handwritten Kannada digit dataset, classification, transfer learning, deep learning.

I.INTRODUCTION

Handwritten Kannada numeral recognition is a task that involves utilizing deep learning methods to recognize handwritten numerals in the Kannada language. This process is particularly challenging due to the variations in handwriting styles, the use of different writing utensils, and the presence of noise and distortions in the handwritten images. Deep learning models, leveraging the power of neural networks, are well-suited for this task as they can effectively capture intricate patterns and representations. The accurate recognition of Kannada numerals is of utmost importance in various industries such as finance, banking, and telecommunications, where automated processing of numerical data is essential for efficient operations. Inspired by the work of P. Goel et al. (2023) [12].

The recognition of handwritten Kannada numerals holds immense potential for enabling many different applications. In the finance sector, accurate recognition of Kannada numerals can automate tasks such as check processing, invoice management, and financial document analysis. Banking institutions can benefit from automated digit recognition for tasks like form processing, account management, and transaction verification. Moreover, in the telecommunications industry, efficient recognition of Kannada numerals can enhance customer experience through automated bill processing, call detail record analysis, and data entry automation. Overall, the advancements in deep learning-based Kannada numeral recognition have paved the way for intelligent systems that streamline operations, reduce manual effort, and improve overall efficiency in various sectors.

The main contribution of my research is as follows:

- Investigation of transfer learning scenarios using pre-trained CNNs for Kannada handwritten numeral classification.
- Evaluation of various pre-trained CNN models to identify the most suitable architecture for accurate Kannada numeral recognition.
- Rigorous assessment of classification performance, highlighting accuracy, robustness, and generalization capabilities of the developed models.
- Demonstration of the practical implications of Kannada numeral classification in finance, banking, and telecommunications sectors.
- Recommendations for further optimization and future research, including exploring advanced CNN architectures and fine-tuning strategies.

II.LITERATURE SURVEY

A. B. M. Ashikur Rahman**,** Md. Bakhtiar Hasan, Sabbir Ahmed , Tasnim Ahme, Md. Hamjajul Ashmafee, Mohammad Ridwan Kabir **and** Md. Hasanul Kabir they studied a thorough examination of the difficulties and ambiguities Bengali HDR and reviews contemporary datasets and methods for offline BHDR over the last two decades. The authors discuss the potential use of contextual information and benchmark datasets with various modalities in biometric applications, and highlight the importance of augmentation techniques for Pipes that are strong and effective in a variety of conditions. The paper also examines the transition from traditional machine learning methods to deep learning methods and highlights they need to carefully consider model architectures and hyperparameters for better performance. Additionally, the authors discuss Real-world application-specific BHDR studies recommend the usage of BHDR pipelines in a number of scenarios to connect the physical and digital worlds.

A. Vanani ,V. Patel, K. Limbachiya and A. Sharma they studied the development of an OCR method identifying for handwritten Gujarati characters and no's using Deep Learning approach. The authors used AlexNet, GoogLeNet , VGG16, and LeNet-5 were only a few examples of CNN architectures for classification models. A bespoke CNN architecture was also suggested, and it produced the highest accuracy for predictions.. The dataset used consisted of more than 18,000 images of handwritten Gujarati numerals, and The specially created convolutional neural network had the best performance of 99.81%. The research demonstrates that the suggested method beat well-known networks like VGG and GoogleNet, which were unable to perform effectively due to their complexity and depth. Overall, the paper demonstrates the effectiveness of Deep Learning approaches and custom CNN architectures for accurate and efficient OCR of handwritten Gujarati numerals.

P. Goel and A. Ganatra they focused on the problem of recognizing handwritten digits in the Gujarati language, which is relatively unexplored compared to other Indian languages. The authors propose a framework that utilizes transfer learning by fine-tuning pre-trained CNN networks, such as ResNet50, ResNet101, InceptionV3, VGG16, VGG-19, and EfficientNet, for feature extraction and categorization. A self-created dataset of Gujarati handwritten digits is used to test the suggested framework, and the findings demonstrate that EfficientNet attained the maximum accuracy among all six networks with prior training. The suggested framework performed better than existing pre-trained networks in terms of recall, F1-Score, precision, recall, and training accuracy. According to the authors, the suggested framework can be expanded to include there are more pretrained CNN models for the Gujarati Handwritten Digit Dataset as well as for the categorization of numerals or characters in other regional languages.

K. Kaur ,R. Dhir and K. Kumar they studied the application of transfer learning techniques using ResNet50 architecture in ultra- Classification of multiclass images using a deep neural network of handwritten digits. The MNIST dataset was used, and the images were normalized in a box of 224x224 pixels using an anti-aliasing technique for better recognition rates. Developers can retrain an existing model to solve a related problem using transfer learning with few modifications, providing a head start and faster results compared to traditional approaches of building models from scratch. The use of transfer learning achieved an accuracy of 99% in a few epochs, which is a significant improvement compared to traditional approaches that require a lot of time to train the dataset. The paper concludes that further accuracy enhancement may be possible by training the dataset for more epochs on desired architectures such as ResNet50.

Al-Mahmud, A. Tanvin and S. Rahman they focused on developing a Convolutional Neural Network (CNN) architecture for recognizing English capital letters and numbers written by hand. The researchers improved upon an existing by modifying the hyperparameters and reducing model overfitting, CNN architecture. On the MNIST digit dataset, where they evaluated their experiments, they attained a test accuracy of 99.47%, which was higher than other techniques used in the study. They also introduced a new dataset for identifying capital letters in English and achieved an accuracy of 98.94% on this dataset. The results show that optimizing hyperparameters can increase accuracy, and they also indicate that longer training cycles and more computing power may lead to even higher precision in the future.

J. Bharvad , D. Garg and S. Ribadiya they focused on the challenge of recognizing handwritten characters, specifically Gujarati handwriting digits, and compares various machine learning techniques used for this purpose. The authors explain that offline handwriting recognition is a tedious task for machines and highlight the importance of creating a solid OCR algorithm to prevent manual entry of important documents. The paper notes that recognizing Gujarati Due to each person's individual writing style and handwriting, commercially available Gujarati script OCR software does not allow for 100% accuracy. Characters with multiple modifiers and specifically linked or joint characters are difficult. The authors discuss the past two decades of research in the field of Gujarati character recognition and conclude that the performance of algorithms varies depending on the dataset used. They suggest that future work should consider the same dataset and implement all techniques to create a comparison table to determine which technique is suitable for which dataset.

X. Wu, Y. Ji and X. Li they studied an improved CNN model for recognizing handwritten numbers based on the sophisticated activation function and Adam optimizer PReLU. The algorithm aims to address the issues of low accuracy and efficiency in existing SVM and nearest neighbor classification techniques. The model uses the Dropout regularization method to improve generalization ability and reduce overfitting. The model's performance in comparison to other recognition the MNIST dataset, and the experimental outcomes demonstrate that the upgraded CNN model achieves good accuracy and convergence, with a score of 99.60%.

M. Shopon, N. Mohammed and M. A. Abedin they studied an approach to improve the accuracy of Bangla digit recognition using unsupervised pre-training using a deep ConvNet and an autoencoder. The proposed model was tested with two standard Bangla character datasets and achieved results for the CMATERDB that are up to date, dataset are excellent outcomes for the ISI dataset. The paper demonstrates that unsupervised Even when datasets are independently generated, pretraining can be effective collected and the proposed approach outperforms models without autoencoders. Future research can examine whether pre-training on larger datasets is beneficial can lead to even better results.

Z. Zhong, L. Jin and Z. Xie they studied a brand-new deep learning model dubbed HCCR-GoogLeNet that's intended to read handwritten Chinese characters. Using four Inception modules to create a productive deep network, the model has a highly deep yet thin architecture. The authors also investigate the use of conventional feature extraction techniques, like gradient or Gabor feature maps, to improve the performance of the convolutional neural network (CNN) for HCCR. The proposed HCCR-GoogLeNet model achieves 96.35% accuracy in modern recognition for a single model and 96.74% for an ensemble model on the offline HCCR competition dataset for ICDAR 2013, surpassing previous best results with a significant gap. Additionally, The accuracy and storage performance are both improved, and the lowest testing error rate ever recorded (3.26%) establishes a new benchmark.

H. Zunair, N. Mohammed and S. Momen they studied unconventional transfer learning approaches for classifying pictures of lone Bangla no’s in the NumtaDB Bengali handwritten digit datasets, achieving In the

Kaggle Numta competition, sixth place. The proposed approach uses a pre-trained VGG16 model with the addition of a softmax layer with a randomly initialized softmax layer and freezing it resulted in better outcomes than conventional transfer learning. Another approach involves freezing layers 16-20 and jointly training beginning layers of the VGG16 model and the softmax layer, which outperformed all other configurations in terms of average accuracy. In addition, compared to CFG-B, this method only needed half as many trainable parameters and epochs. By freezing intermediate layers, it was possible to achieve a precision of 97.09% on the test set for the NumtaDB Bengali handwritten digit datasets, is the best result mentioned in the study. The paper concludes by discussing the need for further analysis to better comprehend the causes of the outcomes and to apply similar setups to other common image categorization challenges.

III.METHODOLOGY

A. Data Collection

The dataset used in this study was collected from Kaggle and comprises a total of 10,241 samples[13]. This dataset serves as a valuable resource for training and evaluating the deep learning models developed for Kannada numeral classification. With its substantial size, the dataset provides an extensive range of diverse handwritten Kannada numeral examples, enabling the models to learn and generalize from a wide variety of writing styles and variations. The large dataset size contributes to the stability and dependability of the developed models, ensuring accurate and effective classification Kannada numerals.

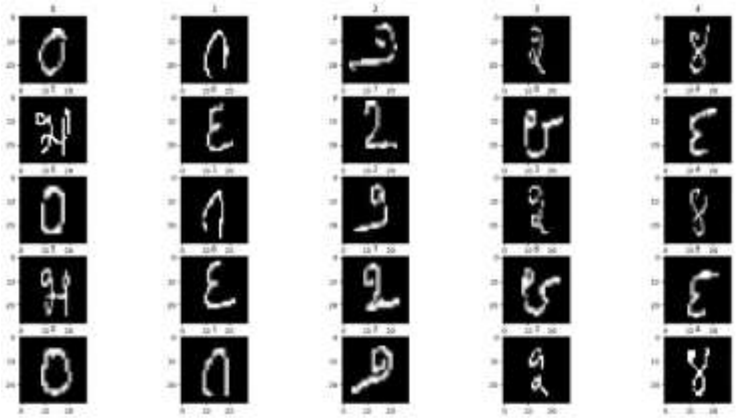

Figure 1: Visualization of the K-MNIST training set

"The grid below showcases 25 grayscale images, each 28x28 pixels in size, from our training dataset. The titles beneath each image indicate their respective class labels, providing a visual glimpse of our dataset's diversity."

B. Feature Extraction

In our research paper, we utilize Conv2D and MaxPool2D layers as crucial feature extraction components in our deep learning model.

Convolutional layers perform local operations on the input data, including computing dot products and sliding a tiny window (kernel) over the input between the kernel and the input patches. This process helps to extract local patterns and features from the pictures entered. how many filters there are in the convolutional layer determines the no of learned features.

Layer max-pooling Decide on the maximum value within each pooling window to use for downsampling the feature maps produced by the convolutional layers. This method minimizes the spatial dimensions of the data while maintaining the most important aspects. Max-pooling aids in capturing translation-invariant features and reducing computational complexity.

Both convolutional and max-pooling layers together act as feature extractors by progressively learning and capturing hierarchical representations of the input images. The early convolutional layers collect low-level data like edges, textures, and gradients, while deeper convolutional layers catch more intricate and abstract information.

C. Building Blocks of CNN Model

The characteristics of our CNN architecture, include dropout, convolutional layers, RELu, max pooling, batch normalization are all described in this section.Convolutional Layer.

The convolutional layer in our CNN model comprises multiple kernels (filters) that serve as feature extractors. These kernels, with dimensions (kw*kh*kd) ,convolve with receptive fields of the input, resulting in feature maps of size (ow*oh). By performing elementwise multiplication and summation, the convolutional layer effectively captures and learns distinctive features from the input data. Notably, our model utilizes kernels with equal width and height, simplifying the computation process. This design choice facilitates accurate recognition of Kannada numerals by effectively extracting relevant visual patterns.

The output dimensions of the feature maps in our CNN model are determined by several key hyperparameters:

- No of Kernels (n): Each kernel correlate with to a feature map, meaning equal depending on how many kernels utilized are the output feature maps. Consequently, the output height (oh) is determined by the number of kernels employed.
- Kernel Width and Height (k): These dimensions define the size of the receptive field, influencing the spatial coverage of the input data. By adjusting the kernel size, we can control the level of detail captured in the feature maps.
- Stride (s): The stride parameter determines the step size at which the kernels traverse the input data's spatial dimensions (width and height) during the convolution process. It affects the spatial downsampling or upsampling of the feature maps.
- Zero Padding (p): Zero padding refers to the additional border of zeros added to the input data, allowing for better preservation of spatial information during convolution. The

padding size influences the output dimensions of the feature maps.

In our CNN architecture, we set s=1 and V=\r ;\ so that iw = ow , ih=oh . This allows us to use an unlimited number of convolutional layers.

Non-linearity

In our architecture, Following each convolutional layer an activation function that introduces non-linearity and improves the network's capacity to handle challenging real-world datasets. Several popular activation functions are available, including tanh, sigmoid function and ReLU. For our CNN architecture, we specifically select the ReLU activation function, represented by f(x)= max(0, x), for its ability to train the network significantly faster compared to alternative options [12]. By utilizing ReLU, our model benefits from faster training times while effectively capturing and learning intricate patterns in the input data, leading to enhanced performance in Kannada numeral recognition.

Max Pooling

Pooling layers are utilized in our CNN architecture to downsize the feature maps, regulating network complexity and preventing overfitting [13]. Specifically, we employ max pooling, dividing the input image into non-overlapping rectangles and selecting the maximum value within each region. To balance information preservation and down sampling, we set the pooling size to (2, 2) and the stride to 2, ensuring no overlap between regions. This process reduces spatial dimensions while retaining important features. By incorporating pooling, our model achieves controlled complexity, mitigates overfitting, and enhances performance in recognizing Kannada numerals.

Ox ,y ,k (0 = max(I2 x,2 y ,k ’I2 x + l,2 y ,k ’I2 x ,2 y + l,k ’I2 x + l,2 y + l,k(1) **(1)**

where Ixyk represents kth input image at (x, y) pixel value and Oxyk represents kth input image at (x-y) pixel value.

ow = iw /2, oh = ih/2, od = id **(2)**

Batch Normalization

The disparity in network activations' distribution brought on by changing network parameters during training is referred to as internal covariance shift. This problem frequently slows down deep neural network training. Our model uses Batch Normalization to reduce this problem and improve training precision [6]. Batch normalization reduces the internal covariance shift by normalizing the input neurons in small batches. Batch Normalization enables smoother and more effective training by smoothing the distribution of activations. Its addition in our model helps our ability to recognize Kannada numerals more accurately.

Dropout

CNNs are prone to overfitting because of the numerous parameters and intricate connections that they use. To address this issue, our model incorporates dropout, an effective regularization technique. Dropout involves temporarily and randomly removing neurons[11], along with their connections, from the neural network with a specified probability (p) [7]. This dropout process allows the model to extract more representative features and reduces the interdependence among features. By applying dropout, our model promotes better generalization and mitigates overfitting, leading to improved performance in recognizing Kannada numerals.

IV.EXPERIMENTAL STUDY

A.CNN Architecture

In our research paper, we propose the "KannadaNumRecogNet," a CNN architecture specifically designed for Kannada numeral identification. The network comprises multiple interconnected layers, including Max-pooling layers, convolutional layers, and thick layers. The convolutional layers, with 32 and 64 filters, extract low-level and higher-level features from input images. A layer called max-pooling follows these layers. that reduces the spatial dimensions while preserving salient information. The flattened output from the completely connected dense layers then get input from the max-pooling layer with 128 and 64 neurons, respectively. These layers enable the network to learn complex relationships among the extracted features. A dropout layer with a dropout rate of 0.2 is added into the architecture to avoid overfitting. During training, this layer at random sets a portion of the inputs to zero, which motivates the network to acquire more robust features. Ten neurons with a softmax activation function make up the output layer, facilitating the classification of Kannada numerals. During training, the network is enhanced with Adam optimizer and sparse categorical cross-entropy loss function are employed in multi-class classification. During training and validation, the model's performance is assessed using the accuracy metric. The proposed KannadaNumRecogNet module demonstrates promising results in accurately recognizing Kannada numerals, offering potential applications in Kannada character analysis, digit recognition, and text processing.

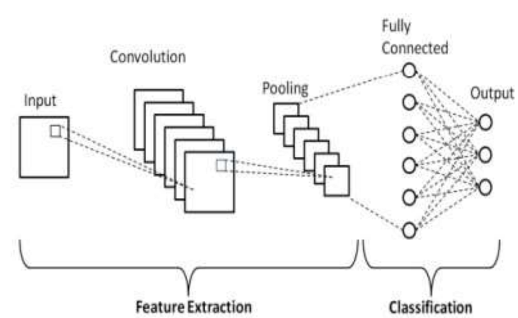

Fig 2: Convolutional Neural Network [14]

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"A Convolutional Neural Network (CNN) is a Deep Learning algorithm used for image analysis. It assigns significance to different aspects of an image and distinguishes between them by learning weights and biases. Unlike some other classification methods, CNNs require less pre-processing. Instead of manually engineering filters, they can learn these features through training."

V.DATASETS

1. Establishing Training and Validation Sets

Our CNN model was trained and validated using the K-MNIST dataset training set, which we received from Kaggle. This dataset contains 60,000 handwritten digits in grayscale, each measuring 28 by 28 pixels. The visuals, which correspond to the digits 0 to 9, are evenly split into 10 categories. The dataset's initial dimensions were 60,000 by 785, with the first column representing each image's label, the following 784 columns, and the values for the pixels. The grayscale image's intensity was represented by these pixel values, which varied from 0 to 255.

The labels in the dataset were extracted and created as one-hot vectors directly from the pixel values prior to the training phase. In addition, all pixel values were normalized by multiplying them by 255 to ensure that they were all between 0 and 1. To recreate the photos, the dataset was then resized to be 60,000 x 28 × 28 x 1. The training set, which included 51,000 photos, and the validation set, which included 9,000 images, were then randomly selected from the dataset. The training set's data underwent additional changes based on the following parameters:

- Range of rotation = 10 degrees,
- Range of zoom = 0.1 (percentage of original size),
- Range of width shift = 0.1 (percentage of the original width),
- Range of height shift = 0.1 (percentage of initial height)

2. Testing Dataset

10,000 grayscale images with a 28 x 28 pixel size make up the K-MNIST dataset's testing set, which was downloaded from Kaggle. The handwritten numbers in these photos, which range from 0 to 9, are evenly dispersed among the several categories. The trained CNN model's effectiveness and accuracy are assessed using the testing set. We may examine the model's accuracy in classifying unknown Kannada numerals by evaluating its predictions on this separate collection of photos.

Before beginning the testing step, the test set's labels and pixel values were split apart and transformed into instantly encoded vectors. Additionally, the pixel values of the test set were adjusted by multiplying each value by 255. Additionally, 10,000 photos with a single channel and 28 by 28 pixel dimensions were added to the test set. The effectiveness and precision of the trained CNN model for recognizing Kannada numerals were evaluated using this standardized and reshaped test set.

VI.RESULTS AND DISCUSSION

Our model gave exceptional results in both the training and validation phases. It attained a training accuracy of 99.75% with a loss of 0.0083 after 30 epochs, while the validation accuracy reached 99.72% with a loss of 0.0124. While the accuracy showed an upward trend over time, there was a trend toward lessening training and validation loss. With an accuracy of 98.77%, the model displayed excellent performance on the testing set. These results show how effectively the model generalizes to different datasets and how well it can recognize Kannada numerals.

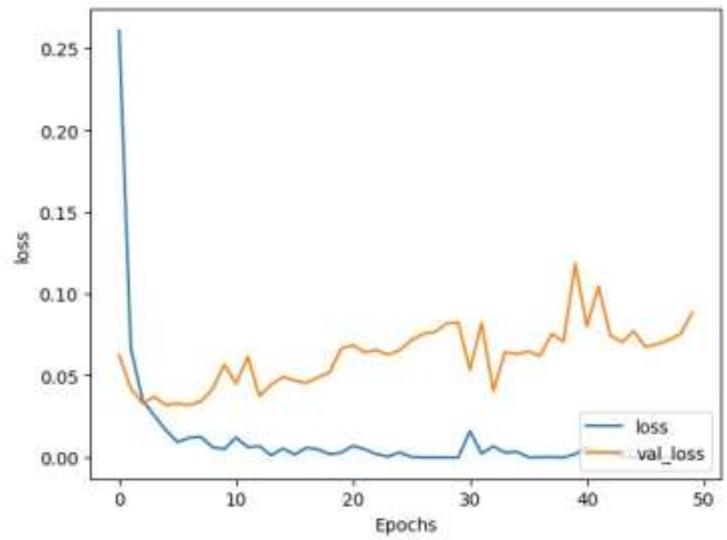

Figure 3: Invalidation and Training Losses

"In the plot, the blue line charts training loss, and the orange line shows validation loss. We want both lines to decrease for effective learning and generalization."

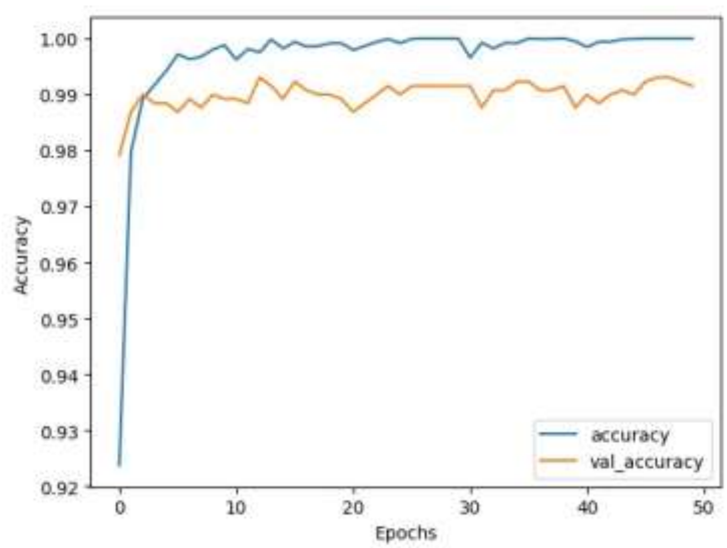

Figure 4: Training and Validation Accuracy

"The graph displays training and validation accuracy. Blue indicates how well the model learns from the training data, and orange represents its performance on unseen data. Our aim is for both lines to ascend, reflecting improved performance."

VII.CONCLUSION AND FUTURE SCOPE

In this study, a CNN model for Kannada number recognition was created and assessed. The model's remarkable accuracy on the training, validation, and testing sets showed how well it could categorize handwritten digits. Convolutional layers' feature extraction abilities and the regularization strategies of batch normalization and dropout helped the model capture significant patterns and avoid overfitting. Through the use of training and validation sets, we were able to assess the model's effectiveness and verify its generalizability.

Our CNN model has shown promising results, but there is room for further research. Future work includes exploring different network architectures and hyperparameter tuning, investigating advanced techniques like transfer learning and ensembles, and utilizing data augmentation methods. Additionally, applying the model to real-world scenarios and optimizing its deployment on resource-constrained devices are important areas for future investigation. These avenues offer opportunities to improve performance, generalization, and practical applicability of the CNN model for Kannada numeral recognition.

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