Project Report for

Kannada MNIST Classification

Recognition for Kannada handwritten digits using CNN

by

Asif Nazir Peshkar

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University of Mysore, Manasagangothri, Mysore– 570006

DECLARATION

I, **Asif Nazir Peshkar,** hereby declare that the Project Report, entitled "**Kannada MNIST Classification**", submitted to the University of Mysore in partial fulfilment of the requirements for the award of the Degree of MCA is submitted to the Directorate of Outreach and Online Programs, University of Mysore and it has not formed the basis for the award of any Degree/Fellowship or other similar title to any candidate of any University.

Place: Navi Mumbai

Date: August 29, 2024

Signature of the Student:

Apeshkar

Acknowledgement

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My deepest appreciation goes to my father, who was born and raised in Karwar, Karnataka. His roots in the Kannada-speaking region inspired me to choose this topic for my project report, even though I am not well-versed in the language myself. His life and experiences have been a constant source of motivation for me.

Lastly, I acknowledge Kaggle for providing the Kannada MNIST dataset, which was essential for this project.

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Abbreviations/Operational definitions used

1. CNN: Convolutional Neural Network - A type of deep learning model particularly effective in image recognition tasks.
2. OCR: Optical Character Recognition - Technology used to convert different types of documents, such as scanned paper documents or images, into editable and searchable data.
3. SVM: Support Vector Machine - A supervised learning algorithm used for classification tasks.
4. KNN: K-Nearest Neighbors - A simple, instance-based learning algorithm used for classification and regression.
5. F1-Score: A measure of a model's accuracy, considering both precision and recall, especially useful in cases of imbalanced data.
6. Precision: The ratio of correctly predicted positive observations to the total predicted positives.
7. Recall: The ratio of correctly predicted positive observations to all observations in the actual class.
8. Epoch: A full cycle through the entire training dataset in model training.
9. Overfitting: When a model performs well on training data but poorly on unseen data due to excessive complexity.
10. Underfitting: When a model is too simple to capture the underlying patterns in the data, resulting in poor performance on both training and unseen data.
11. Data Augmentation: A technique used to increase the diversity of training data without collecting new data, often by applying transformations such as rotation, zoom, and shift to existing data.
12. Learning Rate: A hyperparameter that controls how much to change the model in response to the estimated error each time the model weights are updated.

Chapter 1: Introduction

Overview

Importance of Kannada Digit Recognition: The Kannada language, spoken predominantly in Karnataka, India, has its own unique script, which includes digits different from those in the English numeral system. With the increasing digitization of services, there is a growing need for systems that can accurately recognize and process handwritten Kannada digits. This capability is crucial for applications such as digital document processing, educational software, and automated systems that require input from users in the Kannada language.

Introduction to Kannada Script: Kannada is a Dravidian language primarily spoken in the Indian state of Karnataka. It has a rich literary history dating back over a thousand years. The Kannada script is used for writing the Kannada language, as well as Tulu and other regional languages. The script is an abugida, meaning that each character represents a consonant-vowel combination.

Numeric Characters in Kannada: The Kannada script includes a unique set of numeric characters, which are distinct from the Devanagari and other Indic scripts. These numerals are used in a similar manner to the Western Arabic numerals (0-9) but have their own distinct symbols.

- **0 (೦ - *sonne*):** Represents zero, similar to the concept of zero in other numeral systems.
- **1 (೧ - *ondu*):** The numeral one in Kannada, often used in the same contexts as the digit ‘1’ in Western numerals.

- **2 (೨ - *eradu*):** Represents the numeral two, used in counting and arithmetic operations.
- **3 (೩ - *mooru*):** The digit three in Kannada, visually distinct but functionally equivalent to ‘3’.
- **4 (೪ - *naalku*):** The numeral four, important in both everyday counting and formal arithmetic.
- **5 (೫ - *aidu*):** Represents the number five, widely used across different contexts.
- **6 (೬ - *aaru*):** The digit six, used in the same way as ‘6’ in Western numerals.
- **7 (೭ - *elu*):** Represents the numeral seven, another fundamental digit in Kannada numerals.
- **8 (೮ - *entu*):** The digit eight, used in calculations and various numeric contexts.
- **9 (೯ - *ombattu*):** Represents nine, completing the set of basic numeric characters in Kannada.

Usage in Daily Life: These numeric characters are used in various aspects of daily life in Karnataka, including in educational materials, official documents, and inscriptions. Despite the widespread use of Western numerals, Kannada numerals hold cultural significance and are still taught in schools as part of the language curriculum.

Context and Motivation: In a global context, digit recognition is well-researched with datasets like MNIST for English digits. However, regional languages such as Kannada lack the same level of attention, creating a gap in the availability of robust digit recognition systems. The Kannada MNIST project aims to bridge this gap by developing a model that can accurately classify Kannada handwritten digits, thereby contributing to the broader field of Optical Character Recognition (OCR) for regional languages.

Problem Statement

Objective of the Project: The primary objective of this project is to create a machine learning model, specifically a Convolutional Neural Network (CNN), that can classify images of handwritten Kannada digits with high accuracy. The challenge lies in the distinctiveness of the Kannada script, which differs significantly from the Latin-based characters, necessitating a tailored approach to feature extraction and model training.

Key Questions Addressed:

How can we effectively preprocess the Kannada MNIST dataset to enhance the model's performance?

What CNN architecture is most suitable for recognizing Kannada digits, given their unique shapes and structures?

How can the model be optimized to handle variations in handwriting styles among different individuals?

Expected Outcome: The expected outcome is a CNN model capable of achieving high classification accuracy on the Kannada MNIST dataset. This model could be used in various applications requiring digit recognition in Kannada, such as automated form processing, educational tools, and more.

Significance

Broader Impact: The development of a robust Kannada digit recognition system has significant implications beyond academic interest. It can facilitate the digitization of services in Karnataka, improve accessibility for Kannada-speaking populations, and contribute to the preservation and promotion of the Kannada language in the digital age.

Comparison with Other Datasets: While the original MNIST dataset for English digits is widely known and used in machine learning, the Kannada MNIST dataset introduces unique challenges due to the script's complexity. Unlike Latin-based digits, Kannada digits have intricate curves and shapes that require more sophisticated preprocessing and model tuning.

Applications: Potential applications of the Kannada digit recognition model include:

- Automated Document Processing: Digitizing handwritten forms and records in Kannada.
- Educational Software: Assisting students in learning and writing Kannada digits.
- Assistive Technology: Helping visually impaired individuals understand handwritten Kannada content through audio or tactile feedback.

Scope of the Project

Data Preprocessing: The project will begin with preprocessing the Kannada MNIST dataset, including normalizing the pixel values, augmenting the data to create a more robust training set, and reshaping the images to fit the CNN input format.

- Example Visualization: Below is an example of how the handwritten Kannada digits appear in the dataset:

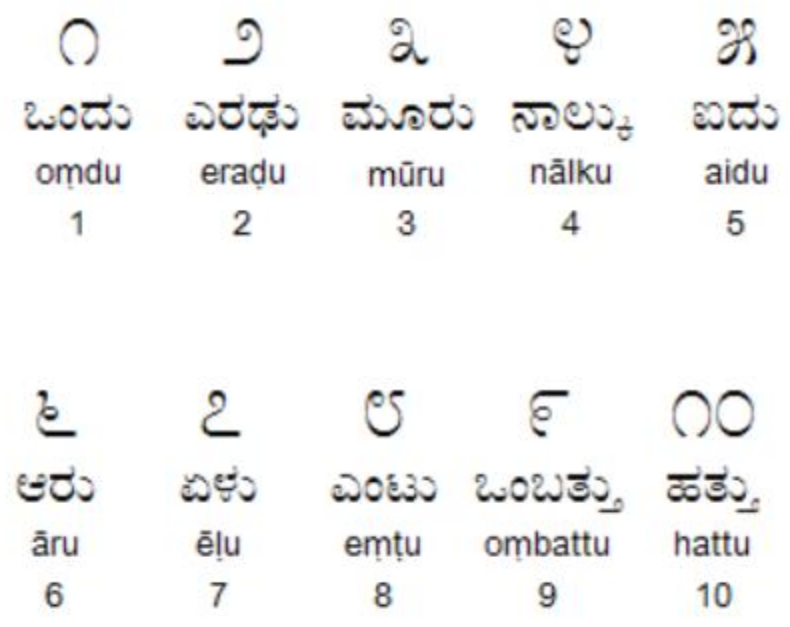


Figure 1.1: Sample images of handwritten Kannada digits from the dataset.

Model Development: The core of the project will involve designing and implementing a CNN tailored to the Kannada digit recognition task. This involves selecting the appropriate architecture, such as using multiple convolutional layers followed by pooling and fully connected layers.

- Example Architecture: The CNN will consist of three convolutional layers, each followed by a max-pooling layer, and then fully connected layers leading to a softmax output for classification.

Evaluation and Optimization: The model will be evaluated using metrics such as accuracy, precision, recall, and F1-score. The goal is to achieve high performance on the test set, with particular attention to minimizing misclassifications.

Example Visualization: A confusion matrix will be used to analyze the model's performance across different digit classes. The confusion matrix is a tool used to evaluate the performance of a model and is visually represented as a table. It provides a deeper layer of insight to data practitioners on the model's performance, errors, and weaknesses. This allows for data practitioners to further analyze their model through fine-tuning.

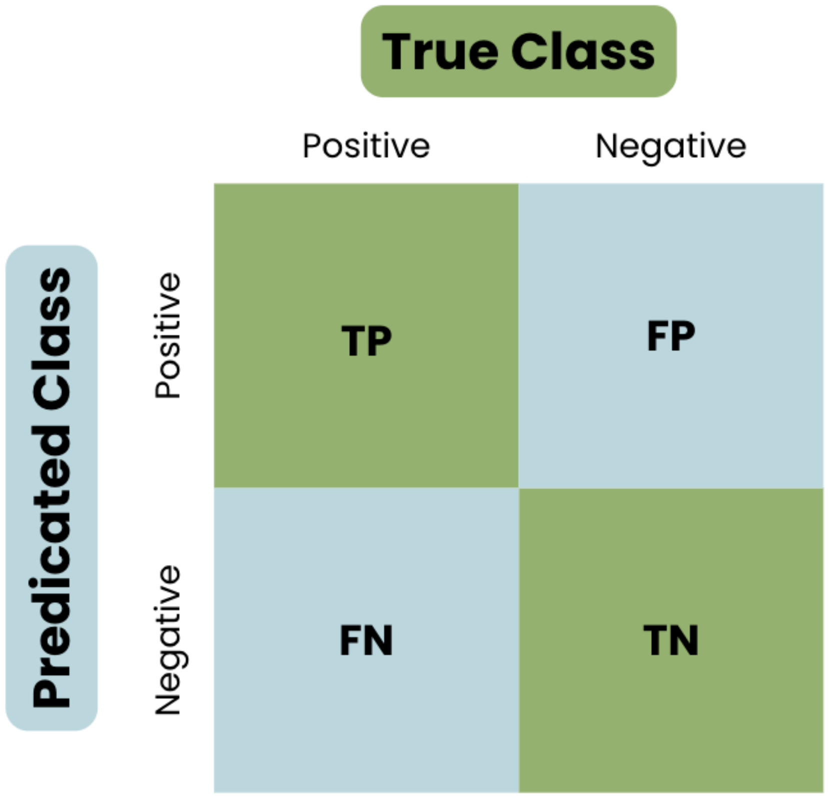


Figure 1.2: Example confusion matrix showing the classification performance.

Challenges

Handwriting Variability: One of the primary challenges is the variability in handwriting styles among different individuals. This variability can lead to misclassifications if the model is not robust enough to generalize across different styles.

- Example Visualization: The following images show variations in how different people write the digit "4" in Kannada:

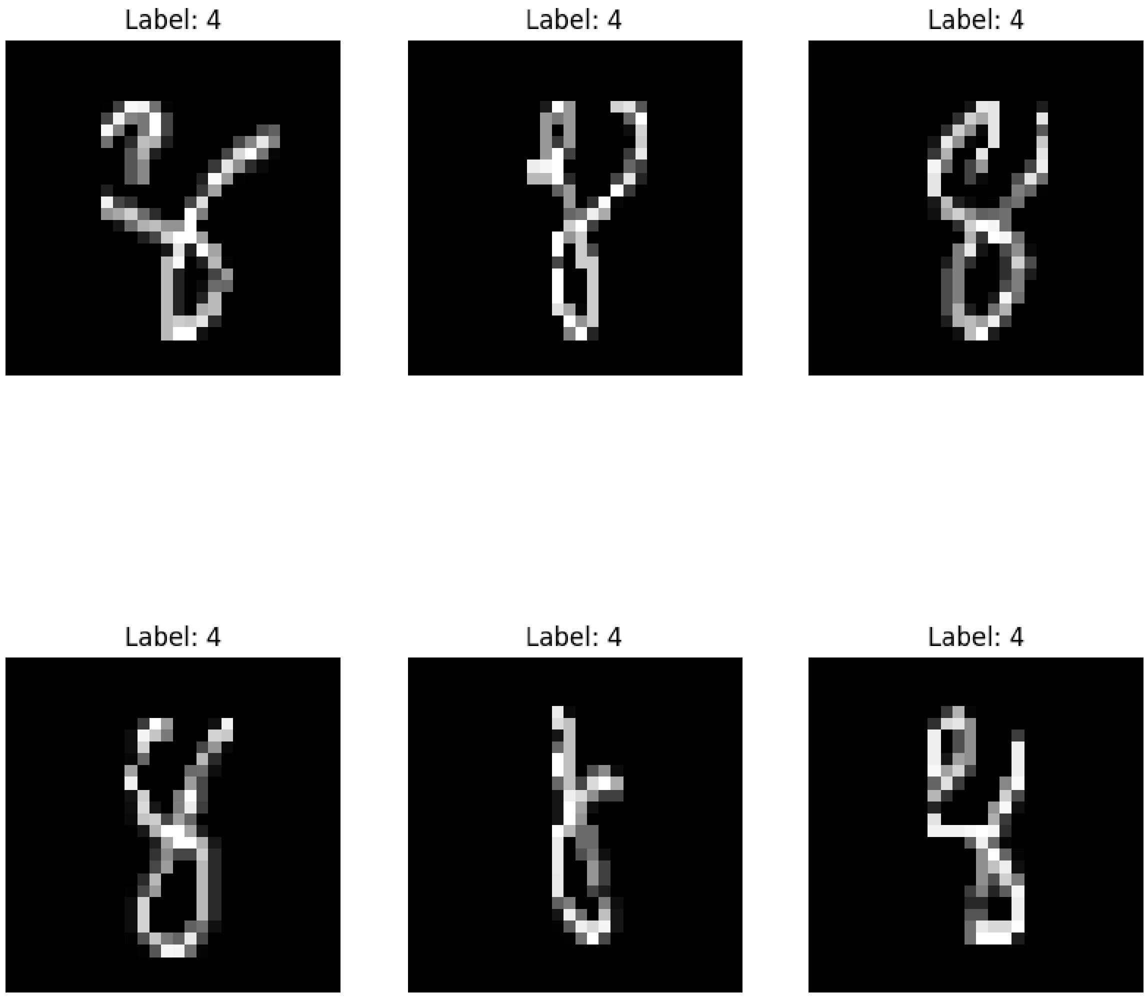


Figure 1.3: Examples of handwriting variability in the Kannada digit "4".

Feature Distinction: Distinguishing between visually similar digits is another challenge. For example, certain Kannada digits may appear similar due to their curves and strokes, making it difficult for the model to differentiate them accurately.

Generalization: The model must be trained to generalize well across various contexts, ensuring that it can handle diverse handwriting inputs without significant loss of accuracy.

Company Profile

As this project is not affiliated with any specific company, the focus remains on its academic and research contributions. The project is part of a broader effort to advance machine learning techniques in the context of regional language processing, particularly in Kannada.

Research Context: The project contributes to the growing body of work in OCR for regional languages. By addressing the unique challenges of Kannada digit recognition, this work will provide insights that could be applied to other regional scripts, furthering the development of inclusive technologies.

II. Research Objectives

In this project, we have formulated the following research objectives using the Knowledge, Skills, and Abilities (KSA) model:

1. Knowledge:

Objective 1: To understand and apply the principles of Convolutional Neural Networks (CNNs) in the context of handwritten digit recognition, specifically focusing on the Kannada script.

2. Skills:

Objective 2: To develop and fine-tune a CNN model capable of accurately classifying Kannada digits, leveraging Python and machine learning frameworks such as TensorFlow/Keras.

Objective 3: To implement data preprocessing techniques, including normalization and data augmentation, to enhance the robustness and accuracy of the model.

3. Abilities:

Objective 4: To evaluate the model's performance using various metrics (accuracy, precision, recall, F1-score) and optimize it for real-world applications.

Objective 5: To analyze the results and identify areas for improvement, with a focus on enhancing the model's generalization capability across different handwriting styles.

III. Research Methodology

Basic Research Design

Objective: The primary objective of this research is to develop and evaluate a Convolutional Neural Network (CNN) model for classifying Kannada handwritten digits. The research is designed to follow an experimental approach, where different models and preprocessing techniques are tested and evaluated to identify the most effective method for digit recognition.

Experimental Setup: The research methodology is divided into several stages:

1. **Data Collection and Preprocessing:**
   - **Data Source:** The Kannada MNIST dataset from Kaggle is used as the primary data source, containing images of handwritten Kannada digits.
   - **Data Preprocessing:** Involves normalizing pixel values, reshaping images, and augmenting the dataset to improve model performance.
2. **Model Development:**
   - **Model Design:** A CNN architecture is designed specifically for this classification task, with multiple convolutional layers followed by pooling layers and fully connected layers.
   - **Training:** The model is trained using the preprocessed data, with the dataset split into training and validation sets to monitor performance and adjust hyperparameters.
3. **Evaluation:**
   - **Metrics:** The model is evaluated using accuracy, precision, recall, and F1-score. A confusion matrix is also used to visualize the model's performance across different classes.

- **Optimization:** Based on the evaluation, the model is further optimized by adjusting parameters such as learning rate, batch size, and network depth.

Secondary Research Design

Literature Review: Secondary research involves a comprehensive review of existing literature on digit recognition using CNNs, focusing on datasets similar to Kannada MNIST. This review includes:

- **Comparison of Techniques:** Examining different CNN architectures and their effectiveness in digit classification tasks.
- **Analysis of Preprocessing Methods:** Reviewing various preprocessing techniques used in previous research to enhance model performance.

Data Collection and Sources:

- **Primary Data:** The Kannada MNIST dataset is the primary data source, consisting of 60,000 training images and 10,000 test images, each representing a 28x28 pixel grayscale image of a handwritten digit.
- **Secondary Data:** Additional resources include academic papers, articles, and online tutorials that provide insights into the best practices for CNN implementation in digit recognition.

Sampling Design: Since the research focuses on model development rather than a survey, traditional sampling methods are not applicable. However, the dataset is divided into training (80%) and validation (20%) sets to evaluate the model's performance. This split ensures that the model is tested on data it hasn't seen during training, providing an accurate measure of its generalization capability.

Techniques of Data Analysis: The data analysis involves several key techniques:

1. **Normalization:** Scaling the pixel values to a range of [0, 1] to facilitate faster convergence during model training.
2. **Data Augmentation:** Applying transformations such as rotation, shift, and zoom to artificially increase the dataset size and improve model robustness.
3. **Model Evaluation:** Using metrics like accuracy, precision, recall, and F1-score to assess model performance. The confusion matrix is particularly useful in understanding misclassifications and identifying areas where the model needs improvement.

Tools and Technologies:

- **Programming Language:** Python is used for the entire implementation process.

- **Libraries and Frameworks:** TensorFlow/Keras for building and training the CNN, Pandas for data manipulation, and Matplotlib/Seaborn for visualization.

- **Development Environment:** Jupyter Notebook or Google Colab for interactive coding and visualization.

Summary: The research methodology combines both experimental and secondary research to develop a robust Kannada digit classification model. By leveraging existing literature and applying state-of-the-art CNN techniques, the project aims to create a model that not only performs well on the Kannada MNIST dataset but also contributes to the broader field of regional language digit recognition. The systematic approach to data collection, preprocessing, model training, and evaluation ensures that the research objectives are met comprehensively.

IV. Limitations of the Project Study

While the Kannada MNIST classification project aims to develop an accurate and robust model for digit recognition, several limitations exist that may impact the study's outcomes:

1. Dataset Constraints:
    - The Kannada MNIST dataset, while comprehensive, may not capture the full diversity of handwriting styles. This could limit the model’s ability to generalize to all possible variations in real-world scenarios.

2. Model Complexity:
    - The CNN model employed, although effective, might not be the most advanced or optimal architecture for this task. Exploring more complex models like deeper networks or transfer learning could potentially yield better results but were not within the scope of this study.

3. Computational Resources:
    - The training of deep learning models requires significant computational resources. Due to resource limitations, the model training was conducted using available hardware, which may not match the performance of models trained on high-end GPUs or distributed systems.

4. Evaluation Metrics:
    - The evaluation metrics used, such as accuracy, precision, recall, and F1-score, provide a comprehensive view of model performance. However, these metrics alone may not fully capture the model's robustness in different practical applications, such as real-time digit recognition or noisy input conditions.

5. Applicability to Other Languages:
    - The model developed is specific to the Kannada script and may not perform well when applied to digits from other regional languages or scripts without significant retraining or adaptation.

Chapter 2: Literature Review

1. Introduction to Digit Recognition and OCR

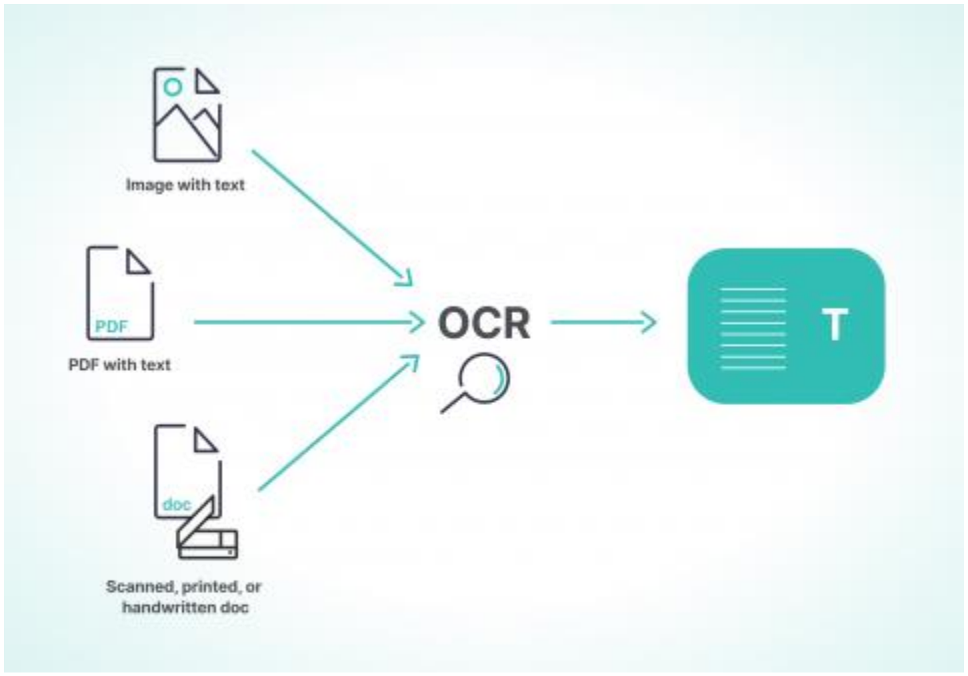


Figure 2.1: General representation of the OCR

- **Theoretical Background:**
    - Overview of Optical Character Recognition (OCR) technology.

      Optical Character Recognition (OCR) technology is a pivotal tool in the field of pattern recognition and computer vision, enabling machines to convert various types of documents—such as scanned paper documents, PDFs, or images taken by a camera—into editable and searchable data. At its core, OCR works by analyzing the shapes and patterns of text characters within an image and converting them into machine-encoded text. This technology has vast applications ranging from digitizing books and automating data entry to enhancing accessibility for visually impaired individuals by converting printed text into speech. The development of OCR has significantly advanced with the advent of deep learning techniques, making it more accurate and capable of recognizing a wide range of fonts and languages, including complex scripts like Kannada.

- Importance of OCR in various applications, especially in regional languages like Kannada.

  The importance of OCR in various applications is immense, especially as it enables the efficient digitization and processing of printed text across a wide range of sectors. In industries such as banking, healthcare, and education, OCR streamlines workflows by converting paper-based information into digital formats that can be easily searched, edited, and stored. This technology is particularly crucial in preserving regional languages like Kannada, which may not have extensive digital resources. OCR allows for the digitization of historical documents, books, and newspapers in regional languages, thereby safeguarding cultural heritage and making these resources more accessible. Moreover, in regions where Kannada is predominantly spoken, OCR facilitates the automation of administrative processes, enabling the local population to interact with digital systems in their native language. This fosters greater inclusivity and ensures that technological advancements benefit a broader spectrum of society.

- **History and Evolution:**
    - Early methods of digit recognition.

Early methods of digit recognition laid the groundwork for the advanced techniques used in modern OCR systems. These methods typically relied on basic pattern recognition and feature extraction techniques. One of the earliest approaches involved template matching, where an input digit image was compared against a set of predefined templates representing each digit. The closest matching template would determine the recognized digit. Another common method was feature-based recognition, where specific characteristics of the digit, such as the number of strokes, intersections, and geometric shapes, were extracted and used to classify the digit. These early methods, though relatively simple, faced limitations in handling variations in handwriting, noise, and distortion in the images. However, they provided a foundation for more sophisticated algorithms, eventually leading to the development of neural networks and deep learning models that revolutionized the field of digit recognition.

- **Transition from rule-based to machine learning approaches.**

  The transition from rule-based to machine learning approaches marked a significant evolution in the field of OCR and digit recognition. Rule-based systems, which dominated the early stages of OCR development, relied heavily on predefined rules and heuristics to interpret and classify text. These systems required extensive manual tuning and were highly sensitive to variations in font styles, noise, and distortions. As a result, their accuracy was limited, particularly when dealing with diverse and complex datasets.

- The advent of machine learning brought a paradigm shift by enabling systems to learn from data rather than relying solely on hand-crafted rules. Machine learning models, especially those based on neural networks, could automatically identify patterns and features within the data, improving accuracy and adaptability. This shift allowed OCR systems to handle a broader range of inputs, including handwritten and cursive text, with much greater precision. The transition culminated in the development of deep learning techniques, such as Convolutional Neural Networks (CNNs), which further enhanced the capability of OCR systems by allowing them to learn hierarchical features directly from raw pixel data, significantly improving performance across various applications, including digit recognition in regional languages like Kannada.

2. Convolutional Neural Networks (CNNs)

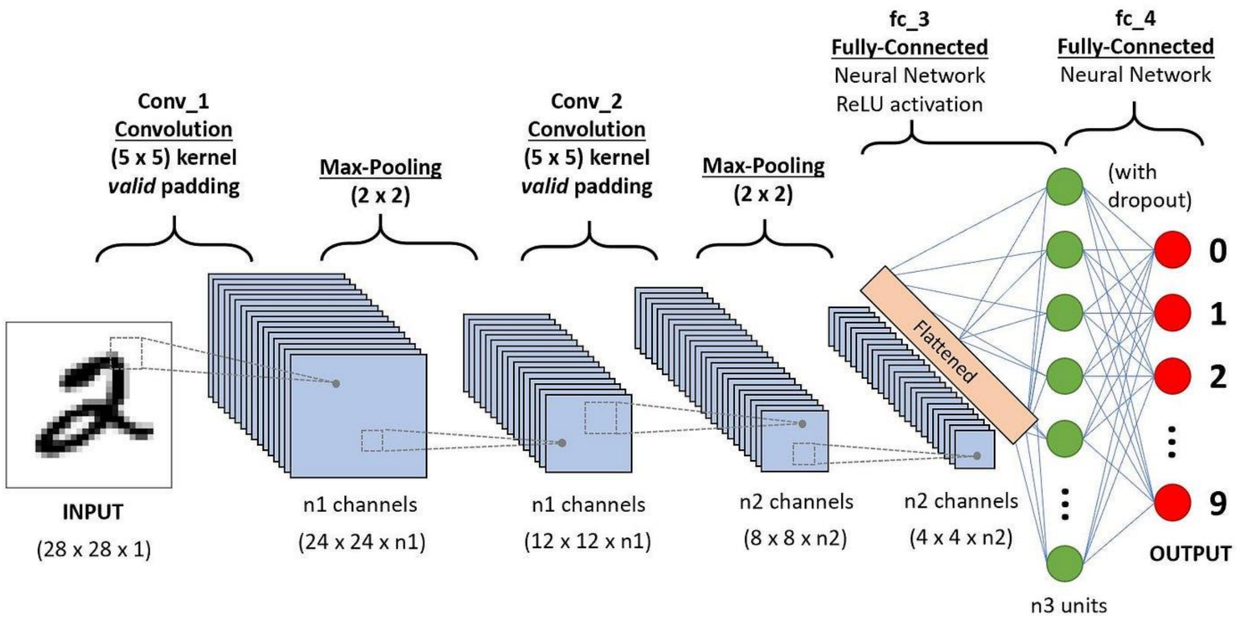


Figure 2.2: A 3D representation of the Convolutional Neural Network

- Fundamentals of CNNs:
    - Architecture of CNNs: Convolutional layers, pooling layers, and fully connected layers.

      The architecture of Convolutional Neural Networks (CNNs) is designed to automatically and adaptively learn spatial hierarchies of features from input images. This architecture typically consists of three main types of layers: convolutional layers, pooling layers, and fully connected layers, each playing a crucial role in the network's ability to recognize patterns and make accurate predictions.

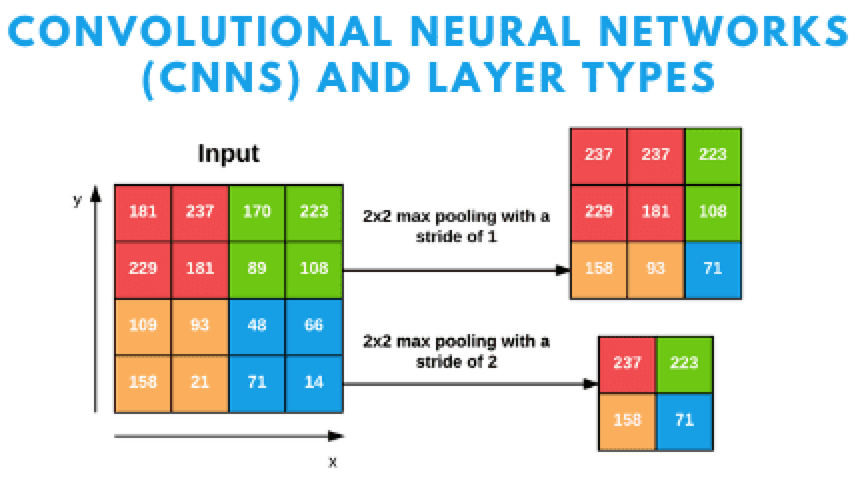

CONVOLUTIONAL NEURAL NETWORKS (CNNS) AND LAYER TYPES
Input
y
x
181 237 170 223
229 181 89 108
109 93 48 66
158 21 71 14
2x2 max pooling with a stride of 1
237 237 223
229 181 108
158 93 71
2x2 max pooling with a stride of 2
237 223
158 71

Figure 2.3: CNN Layer Types.

1. Convolutional Layers: These layers are the core building blocks of a CNN. They apply a set of filters (also known as kernels) to the input image, sliding across it to create feature maps. Each filter is designed to detect specific features such as edges, textures, or colors. The convolution operation captures local patterns and spatial hierarchies, making it especially effective for tasks like image recognition. The output of this layer is a set of feature maps that highlight the presence of various features in different regions of the input image.
2. Pooling Layers: Pooling layers are used to reduce the spatial dimensions (height and width) of the feature maps generated by the convolutional layers, while retaining the most important information. This process, known as downsampling, helps to make the network more computationally efficient and less sensitive to small translations or distortions in the input image. The most common type of pooling is max pooling, which selects the maximum value from each region of the feature map, effectively reducing the data size while preserving important features.
3. Fully Connected Layers: After several convolutional and pooling layers, the high-level reasoning in the network is performed by fully connected layers. These layers are similar

to those in traditional neural networks, where each neuron is connected to every neuron in the previous layer. The fully connected layers interpret the features extracted by the convolutional and pooling layers and combine them to make the final classification or prediction. The last fully connected layer typically outputs a probability distribution over the possible classes, allowing the network to make a decision about what the input image represents.

This layered approach enables CNNs to excel at tasks such as image and digit recognition, including challenging datasets like the Kannada MNIST, by effectively capturing and processing complex visual information.

- How CNNs mimic the human visual cortex.

  Convolutional Neural Networks (CNNs) are often said to mimic the human visual cortex due to their ability to process visual information in a hierarchical manner, similar to how the human brain interprets images. The visual cortex in the human brain is organized in a series of layers, where each layer is responsible for detecting increasingly complex features of the visual input. CNNs replicate this layered approach, allowing them to effectively recognize and classify images.

1. Hierarchical Feature Extraction: Just like the visual cortex, CNNs process images in stages. The early layers of a CNN are analogous to the primary visual cortex, which detects basic visual elements such as edges, lines, and simple shapes. As the information moves through the layers of the CNN, the network begins to recognize more complex patterns, much like how the visual cortex identifies shapes, objects, and even faces in its later stages. This hierarchical processing allows CNNs to build up a detailed understanding of an image from simple to complex features.

2. Local Receptive Fields: In the human visual system, neurons in the early stages of the visual cortex respond to stimuli in specific, localized areas of the visual field. CNNs mimic this by using convolutional layers where each neuron (or filter) processes only a

small region of the input image, known as the receptive field. This localized processing allows CNNs to focus on specific parts of an image and detect features such as edges or textures in those areas, which are then combined to form a comprehensive understanding of the entire image.

3. Shared Weights and Pattern Recognition: In both the visual cortex and CNNs, the same pattern recognition mechanisms are applied across different parts of the visual field. In CNNs, this is achieved through shared weights, meaning that the same filter is applied across the entire image to detect a particular feature, regardless of its position. This ability to recognize patterns anywhere in an image is critical for tasks like object detection and digit recognition, mirroring the visual cortex's ability to recognize objects no matter where they appear in the field of vision.

This structural and functional similarity between CNNs and the human visual cortex is what makes CNNs so powerful in tasks that require understanding visual data, such as recognizing handwritten digits in the Kannada MNIST dataset or identifying objects in complex images.

- Relevance of CNNs in image classification tasks.

  Convolutional Neural Networks (CNNs) are highly relevant in image classification tasks due to their ability to automatically learn and extract features directly from raw images. Their architecture, with convolutional layers and pooling, enables them to recognize patterns regardless of their position, making them robust to variations in image data. CNNs have consistently outperformed traditional methods, achieving state-of-the-art accuracy across diverse classification challenges. Their scalability and adaptability through techniques like transfer learning further enhance their effectiveness, making CNNs the preferred choice for a wide range of image classification applications

- CNNs in Digit Recognition:
    - Application of CNNs in the MNIST dataset.
- Convolutional Neural Networks (CNNs) have been widely applied to the MNIST dataset, which consists of handwritten digits, to achieve highly accurate digit recognition. The CNN architecture effectively captures the spatial hierarchies of pixel intensities, allowing it to distinguish between similar digits with high precision. By using convolutional layers to detect features such as edges and curves, pooling layers to reduce dimensionality, and fully connected layers to classify the digits, CNNs consistently achieve near-perfect accuracy on the MNIST dataset. This success has made CNNs the benchmark model for digit recognition tasks and has paved the way for their application in more complex datasets, such as the Kannada MNIST dataset.

    - Extension to regional datasets like Kannada MNIST.

      The success of CNNs on the original MNIST dataset has led to their extension to regional datasets like Kannada MNIST, which focuses on recognizing handwritten digits in the Kannada script. CNNs are particularly effective for such regional datasets due to their ability to learn and generalize from the unique characteristics of different scripts. By applying the same principles of feature extraction and classification used in the standard MNIST, CNNs can adapt to the nuances of Kannada digits, handling variations in handwriting styles and preserving high accuracy. This adaptability makes CNNs a powerful tool for digit recognition across various languages and scripts, supporting efforts to digitize regional texts and improve accessibility.

3. Related Work in Handwritten Digit Recognition

- Key Studies:
  - Review of seminal works on MNIST digit recognition.

    Seminal works on MNIST digit recognition have laid the foundation for modern advancements in machine learning and computer vision. Yann LeCun's pioneering work in the late 1990s introduced Convolutional Neural Networks (CNNs) as a powerful tool for image recognition, with the LeNet-5 architecture becoming a landmark model for digit classification on the MNIST dataset. This model demonstrated the effectiveness of using convolutional layers for feature extraction and pooling layers for dimensionality reduction, achieving high accuracy with relatively simple architectures. Subsequent works built on this foundation, exploring deeper networks, regularization techniques, and optimization methods to further enhance performance. These early contributions not only established CNNs as the go-to approach for digit recognition but also spurred the development of more advanced models that continue to push the boundaries of accuracy and efficiency in image classification tasks.

  - Studies focused on non-Latin scripts (Arabic, Devanagari, etc.).

Studies focused on non-Latin scripts, such as Arabic, Devanagari, and others, have played a crucial role in expanding the applicability of digit recognition technologies to diverse linguistic contexts. Researchers have applied and adapted Convolutional Neural Networks (CNNs) to these scripts, addressing the unique challenges posed by their complex shapes, cursive connections, and variations in stroke patterns. For example, the recognition of Arabic digits, which often involves connected characters and right-to-left writing, has benefited from customized CNN architectures that account for these specific features. Similarly, Devanagari script, with its intricate characters and multiple diacritics, has been effectively tackled using CNNs combined with preprocessing techniques to enhance feature extraction. These studies have not only improved digit recognition accuracy for non-Latin scripts but have also contributed to the development of multilingual OCR systems, making digital text processing more inclusive and accessible across different languages.

- Comparison of Techniques:
    - Traditional machine learning models vs. deep learning approaches.
- Traditional machine learning models rely on manual feature extraction and often struggle with complex, high-dimensional data. In contrast, deep learning approaches, like CNNs, automatically learn hierarchical features directly from raw data, leading to significantly higher accuracy and better generalization, especially in tasks like image recognition and digit classification.

    - Performance benchmarks across various datasets.
- CNNs consistently outperform traditional models across various datasets, including MNIST, CIFAR-10, and ImageNet, achieving state-of-the-art accuracy. Their ability to adapt to different data types and complexities has made them the benchmark standard for evaluating performance in image classification tasks.

4. Data Augmentation and Preprocessing

- Importance in OCR:

How data augmentation improves model generalization.

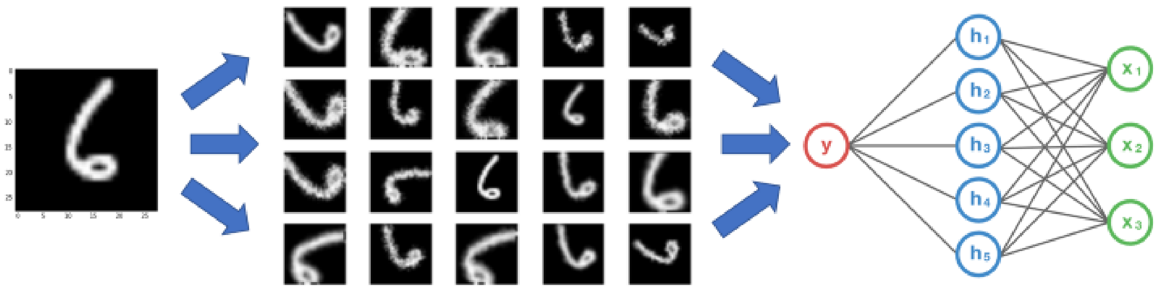


Figure 2.4: Examples of handwriting variability in the Kannada digit.

- Data augmentation improves model generalization by artificially increasing the diversity of the training dataset through transformations like rotation, scaling, flipping, and cropping. This process helps the model become more robust to variations and reduces the risk of overfitting, leading to better performance on unseen data.

  - Common preprocessing techniques: Normalization, noise reduction, etc.

- Common preprocessing techniques like normalization and noise reduction are essential for preparing data for CNNs. Normalization scales pixel values to a consistent range, improving convergence during training, while noise reduction techniques, such as Gaussian blurring, help remove unwanted artifacts, ensuring cleaner input data and enhancing model accuracy.

- Applications in Kannada MNIST:
    - Specific challenges posed by the Kannada script.

      The Kannada script presents specific challenges in digit recognition due to its intricate characters, complex curves, and similarities between different digits. Additionally, variations in handwriting styles and the presence of diacritical marks add to the difficulty, requiring robust feature extraction and classification methods in CNNs to accurately recognize and differentiate between the digits
    - Techniques used in this project to overcome these challenges.
- In this project, techniques such as data augmentation were employed to enhance the diversity of training samples, helping the model generalize better to variations in Kannada handwriting. Additionally, a carefully designed CNN architecture with multiple convolutional and pooling layers was used to effectively capture the intricate features of Kannada digits, improving recognition accuracy despite the script's complexity.

5. Model Optimization Techniques

Hyperparameter Tuning:

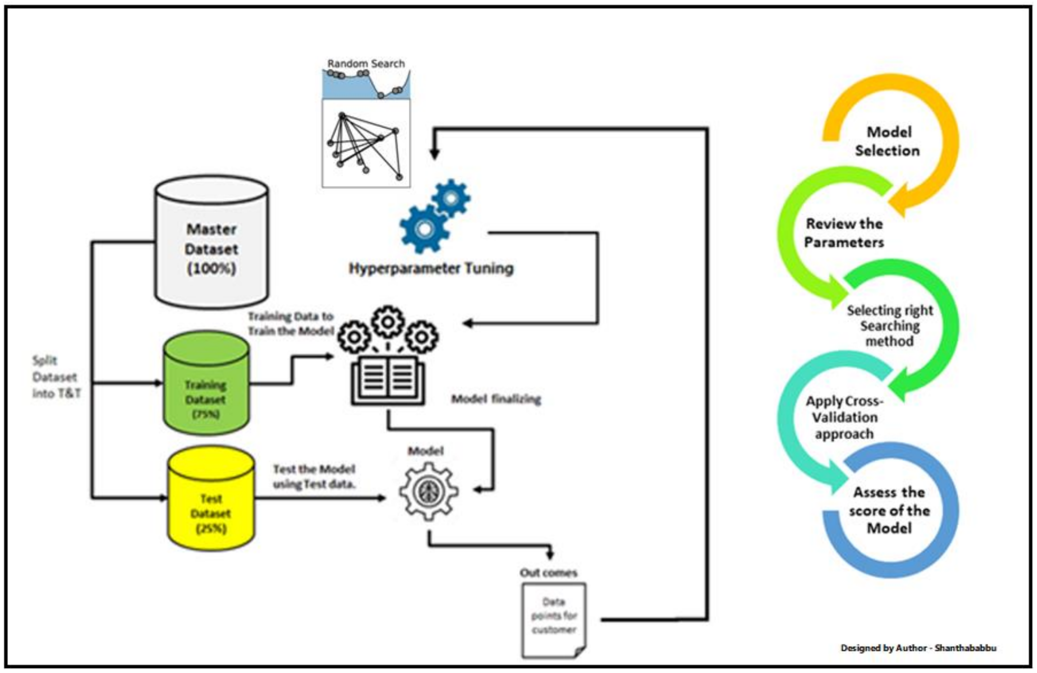


Figure 2.5: Hyperparameter Tuning

- Importance of tuning learning rates, batch sizes, and network depth.

  Tuning learning rates, batch sizes, and network depth is crucial for optimizing CNN performance. The learning rate controls how quickly the model adapts to the data; too high can cause instability, while too low slows down training. Batch size affects the stability and speed of learning, with larger sizes providing more stable gradients but requiring more memory. Network depth determines the model's ability to capture complex patterns; deeper networks can learn more detailed features but are harder to train and more prone to overfitting. Proper tuning of these parameters is essential for achieving the best results in tasks like Kannada digit recognition.

- Techniques like Grid Search and Random Search.

  Grid Search and Random Search are techniques used for hyperparameter optimization in machine learning models. Grid Search exhaustively searches through a specified range of hyperparameters, testing all possible combinations to find the best-performing set. While comprehensive, it can be computationally expensive. Random Search, on the other hand, samples a random subset of hyperparameter combinations, making it more efficient in exploring large spaces, often leading to near-optimal results with less computational cost. Both techniques are valuable for fine-tuning models like CNNs to achieve optimal performance in tasks such as Kannada digit recognition

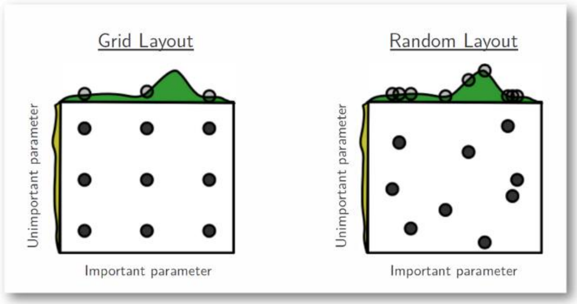


Figure 2.6: Grid Search and Random Search

- Regularization Techniques:
  - Dropout, L2 regularization, and batch normalization.

    Dropout, L2 regularization, and batch normalization are techniques used to improve the performance and generalization of CNNs. Dropout randomly deactivates a fraction of neurons during training, reducing the risk of overfitting by preventing the network from relying too heavily on any single neuron. L2 regularization adds a penalty for large weights in the loss function, encouraging the model to learn simpler patterns that generalize better to new data. Batch normalization normalizes the inputs of each layer, stabilizing and accelerating training, and making the network less sensitive to changes in learning rates. These techniques are essential for building robust models, especially in complex tasks like Kannada digit recognition.

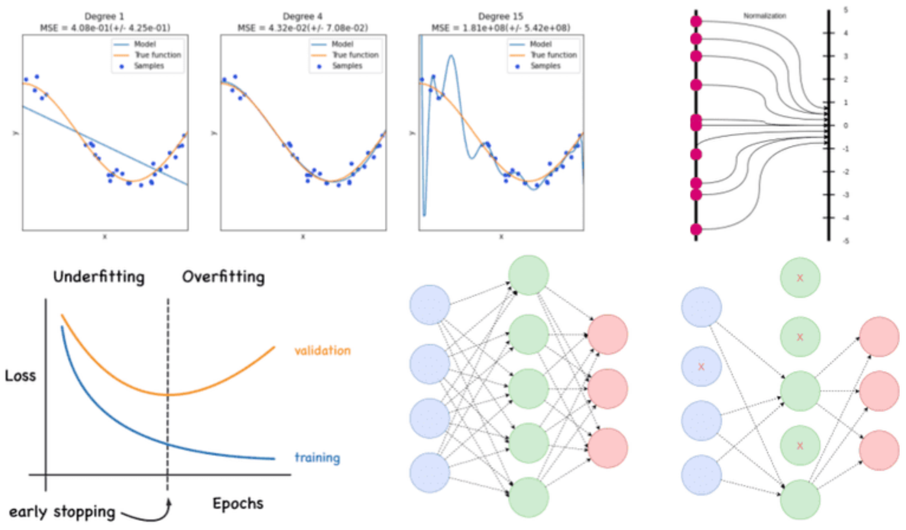
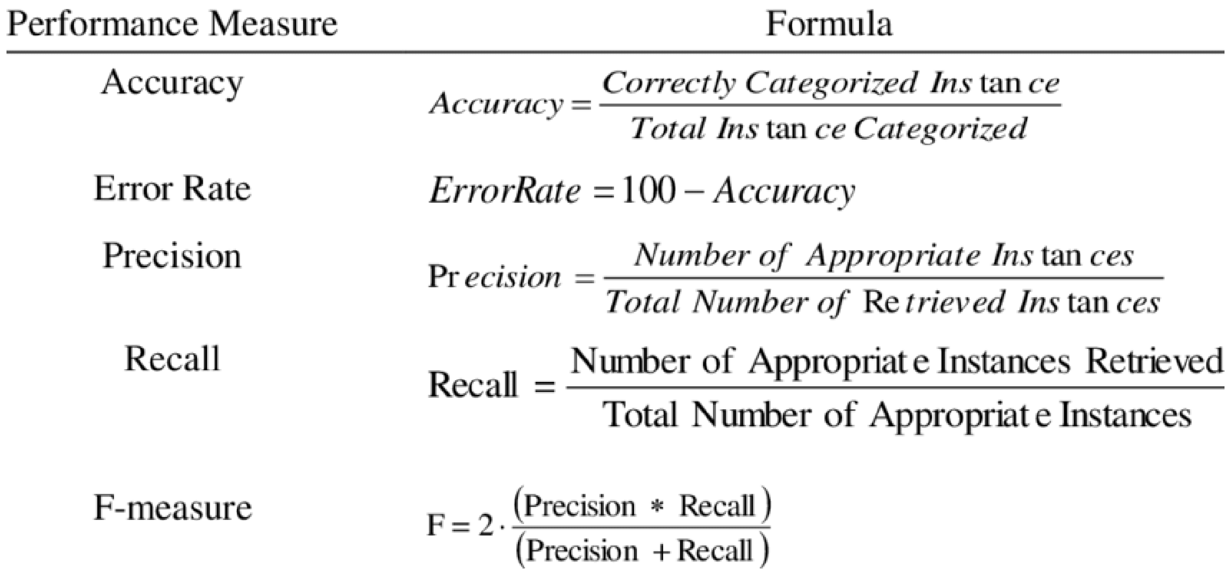


Figure 2.7: Regularization Techniques

- Evaluation Metrics:



Performance Measure	Formula
Accuracy	$Accuracy = \frac{Correctly\ Categorized\ Ins\tan ce}{Total\ Ins\tan ce\ Categorized}$
Error Rate	$ErrorRate = 100 - Accuracy$
Precision	$\mathrm{Pr}ecision = \frac{Number\ of\ Appropriate\ Ins\tan ces}{Total\ Number\ of\ \mathrm{Re}trieved\ Ins\tan ces}$
Recall	$\text{Recall} = \frac{\text{Number of Appropriat e Instances Retrieved}}{\text{Total Number of Appropriat e Instances}}$
F-measure	$\text{F} = 2 \cdot \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$

Figure 2.7: Precision and Recall formulae

- Precision, recall, F1-score, and their significance in model evaluation.

  Precision, recall, and F1-score are key metrics in evaluating a model's performance, particularly in classification tasks. Precision measures the accuracy of the positive predictions, indicating the proportion of true positives among all predicted positives. Recall assesses the model's ability to identify all actual positives, showing the proportion of true positives among all actual positives. F1-score is the harmonic mean of precision and recall, providing a balanced measure that accounts for both false positives and false negatives. These metrics are crucial for understanding the model's effectiveness, especially in imbalanced datasets, ensuring that the model performs well across different aspects of prediction accuracy.

6. Challenges in Regional Language OCR

- Variability in Handwriting:
    - The impact of diverse handwriting styles on model accuracy.
      Diverse handwriting styles significantly impact model accuracy in tasks like digit recognition. Variations in stroke thickness, slant, and character formation can make it challenging for the model to consistently recognize digits, especially in scripts like Kannada. These differences introduce noise and complexity, potentially leading to misclassification. Techniques such as data augmentation and robust feature extraction are essential to mitigate these effects, helping the model generalize better across different handwriting styles and improve overall accuracy.

    - Case studies of regional language OCR efforts.
      Case studies of regional language OCR efforts highlight the unique challenges and successes in digitizing non-Latin scripts. For example, efforts in developing OCR for Devanagari script have focused on overcoming the complexities of connected characters and multiple diacritical marks. Similarly, OCR projects for Arabic script have addressed the challenges posed by cursive writing and varying character shapes. These case studies often demonstrate the importance of customized CNN architectures and advanced preprocessing techniques in achieving high accuracy. Successful implementations in regional languages have significantly contributed to the preservation and accessibility of cultural texts, enabling broader access to digital resources in native languages.

- Feature Extraction in Complex Scripts:
    - Differences between Latin scripts and regional scripts like Kannada.
      Latin scripts and regional scripts like Kannada differ significantly in their structure and visual complexity. Latin scripts generally consist of simpler, more uniform characters with fewer variations in shape, making them easier to recognize. In contrast, Kannada and other regional scripts feature more intricate characters with complex curves, loops, and diacritical marks. Additionally, Kannada characters can vary significantly depending on handwriting style, which adds to the complexity. These differences require more sophisticated feature extraction and recognition techniques in OCR systems to accurately process regional scripts, often necessitating customized CNN architectures to handle the unique challenges they present.

    - How CNNs handle complex features in such scripts.
      CNNs handle complex features in scripts like Kannada by leveraging their multi-layered architecture to progressively extract and process intricate patterns. The convolutional layers capture basic elements such as edges and curves, which are then combined in deeper layers to form more complex representations of the characters. Pooling layers help in reducing the dimensionality, making the model more robust to variations in handwriting. Additionally, the hierarchical structure of CNNs allows them to focus on different aspects of the script at different layers, effectively managing the complexity and variability of Kannada characters, leading to accurate recognition

7. Future Trends in OCR and Machine Learning

- Transfer Learning and Pre-trained Models:
    - How pre-trained models like ResNet and Inception can be adapted for OCR tasks.
      Pre-trained models like ResNet and Inception can be effectively adapted for OCR tasks by leveraging their deep architectures and transfer learning capabilities. These models, trained on large datasets like ImageNet, have already learned a rich set of features that can be fine-tuned for specific OCR tasks, such as digit recognition in regional scripts. By replacing the final classification layer with one tailored to the specific classes of the OCR task and fine-tuning the model on the target dataset, these pre-trained networks can quickly adapt to recognizing complex characters. This approach significantly reduces training time while improving accuracy and performance in OCR applications.

- Role of AI in Multilingual OCR:
    - The potential for AI to handle multiple languages and scripts.
      AI has significant potential to handle multiple languages and scripts by leveraging advanced models like CNNs and transformers, which can learn and generalize across diverse linguistic patterns. Through techniques like transfer learning and multilingual training, AI systems can be trained on datasets that include various languages and scripts, enabling them to recognize and process different writing systems effectively. This capability opens the door to creating universal OCR systems that can handle a wide range of languages, from Latin-based scripts to complex regional scripts like Kannada, making digital text processing more inclusive and accessible globally
- Impact of Emerging Technologies:
    - The role of quantum computing and edge AI in the future of OCR.
      Quantum computing and edge AI are poised to revolutionize the future of OCR

by enhancing processing speed and enabling real-time, on-device text recognition. Quantum computing, with its potential to solve complex problems exponentially faster than classical computers, could significantly improve the efficiency of training deep learning models, leading to faster and more accurate OCR systems. Edge AI, on the other hand, brings the power of AI directly to devices like smartphones and IoT gadgets, allowing OCR tasks to be performed locally without relying on cloud processing. This shift not only improves privacy and reduces latency but also enables OCR to be used in remote or offline environments, expanding its applicability and accessibility.

8. Summary of Theoretical Concepts

- Synthesis of Reviewed Literature:
  - Key takeaways from the literature.

  - Advancement of CNNs: The shift from traditional rule-based methods to CNNs has significantly improved OCR accuracy, particularly for complex scripts like Kannada.
  - Importance of Preprocessing: Techniques like normalization, data augmentation, and regularization are crucial for enhancing model performance and generalization.
  - Adaptation to Regional Scripts: CNNs have been successfully adapted to handle the unique challenges posed by non-Latin scripts, enabling accurate recognition across diverse languages.
  - Emerging Technologies: The potential of quantum computing and edge AI is highlighted as key future developments that could further enhance OCR capabilities, making them faster and more accessible.

- How this project builds on existing knowledge.

  This project builds on existing knowledge by leveraging the proven effectiveness of Convolutional Neural Networks (CNNs) in image recognition, specifically applying these techniques to the Kannada MNIST dataset. It extends the foundational work on CNNs by addressing the unique challenges posed by the Kannada script, such as complex character shapes and handwriting variations. By incorporating techniques like data augmentation, careful hyperparameter tuning, and leveraging advancements like transfer learning from pre-trained models, this project enhances the generalization and accuracy of OCR systems for regional scripts. In doing so, it not only reaffirms the versatility of CNNs but also contributes to the broader application of AI in multilingual and script-diverse contexts

- Gaps in Current Research:
    - Identified gaps that this project aims to address.
      This project aims to address several identified gaps in the field of OCR for regional scripts. First, while significant progress has been made in recognizing Latin-based scripts, there is a relative lack of focus on non-Latin scripts like Kannada, which pose unique challenges due to their complex characters and handwriting variations. Additionally, many existing models struggle with generalization when faced with the diversity of handwriting styles in Kannada. This project seeks to fill these gaps by applying advanced CNN techniques tailored to the Kannada script, enhancing model robustness and accuracy. It also explores the potential of integrating data augmentation and hyperparameter optimization to improve the performance of OCR systems in recognizing complex regional scripts
    - Potential areas for future research.
      Potential areas for future research include exploring the application of more advanced deep learning architectures, such as transformers, for OCR tasks in regional scripts like Kannada. Additionally, research could focus on developing more sophisticated data augmentation techniques tailored to the specific challenges of non-Latin scripts. Another promising area is the integration of quantum computing to accelerate model training and improve efficiency. Finally, expanding the scope of multilingual OCR systems to handle a wider variety of scripts and languages, including underrepresented ones, and improving their real-time performance on edge devices could significantly advance the field.

Methodology Justification

The selection of a Convolutional Neural Network (CNN) for this project was driven by its superior ability to handle image data, particularly in tasks involving handwritten digit recognition. Traditional machine learning models, like Logistic Regression or Support Vector Machines, while effective for simpler tasks, struggle with the complex feature hierarchies in images. CNNs, with their layered structure, excel at learning these hierarchical features, making them the ideal choice for this project. The decision to implement specific preprocessing techniques, such as normalization and data augmentation, was based on the need to enhance model generalization and prevent overfitting. These steps were crucial for achieving high accuracy on the validation set, as they allowed the model to effectively learn from the training data and apply this knowledge to unseen data.

Ethical Considerations and Data Privacy

In the development and deployment of machine learning models, ethical considerations and data privacy are paramount. This project, while focused on the technical aspects of Kannada digit recognition, acknowledges the broader implications of data use and model deployment. The dataset used, Kannada MNIST, consists of publicly available data designed for educational and research purposes, ensuring that no personal or sensitive information is involved. However, in real-world applications, it is essential to consider the ethical implications of using data, particularly when it involves personal information. Issues such as data ownership, consent, and the potential for bias in model predictions must be carefully managed. Moreover, when deploying models in production environments, ensuring that user data is handled securely and that privacy is maintained is crucial. This includes implementing robust data encryption methods, following data protection regulations, and being transparent with users about how their data is used.

Case Study on Real-World Application

Consider a scenario where the Kannada digit recognition model developed in this project is deployed as part of a mobile application for educational purposes. The app could be used by students in Karnataka to practice writing Kannada digits, with the model providing instant feedback on the accuracy of their handwriting. By integrating this model, the app would offer personalized learning experiences, helping students improve their writing skills. Additionally, the model could be used in digitizing handwritten documents, such as historical records or educational materials, preserving Kannada literature and making it more accessible in the digital age. However, deploying such a model in a real-world application would require careful consideration of factors like computational efficiency, to ensure the app runs smoothly on mobile devices, and continuous learning, to update the model as more data becomes available. This case study illustrates the potential impact of the project beyond academic research, highlighting its practical applications in education and digital preservation.

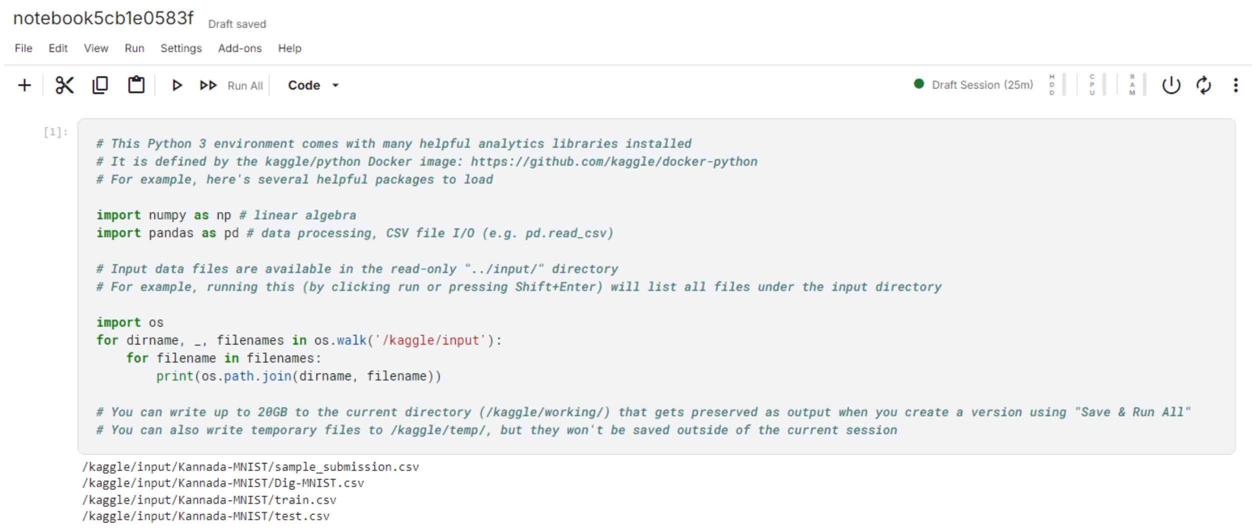
Chapter 3: Findings

Part 1: Data Exploration and Preprocessing Findings

1. Overview of the Dataset:

- The Kannada MNIST dataset consists of 60,000 training images and 10,000 test images, each representing a 28x28 pixel grayscale image of a handwritten Kannada digit.
- The dataset includes ten classes, corresponding to the digits 0-9 in the Kannada script.

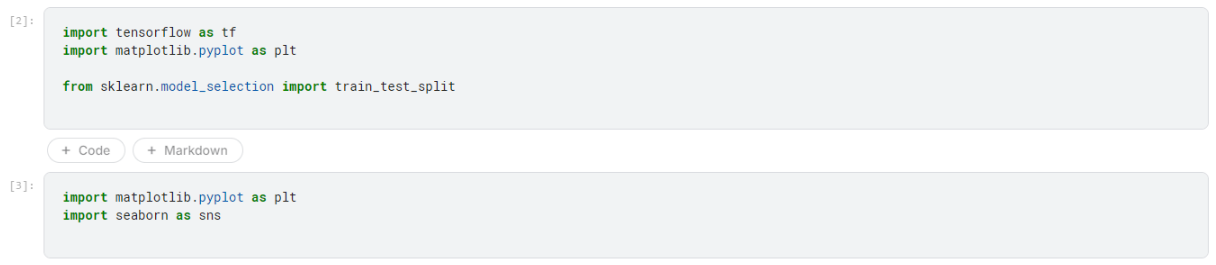
Let's initialize the environment in the Kaggle's website.



```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/Kannada-MNIST/sample_submission.csv
/kaggle/input/Kannada-MNIST/Dig-MNIST.csv
/kaggle/input/Kannada-MNIST/train.csv
/kaggle/input/Kannada-MNIST/test.csv
```

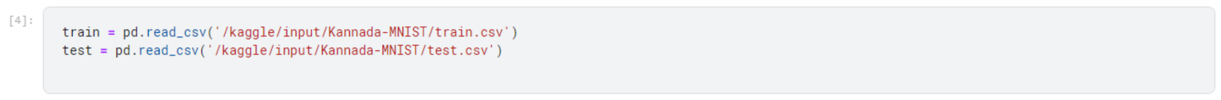
Importing libraries used by the notebook



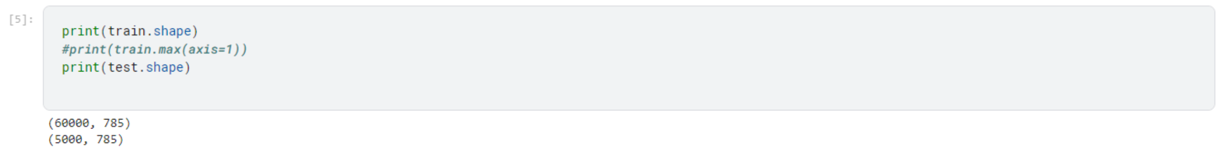
```
[2]:
import tensorflow as tf
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
```

```
[3]:
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading the data and checking the records in the train and test datasets



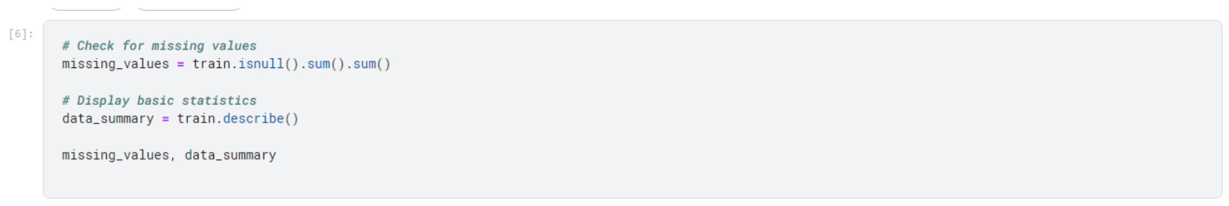
```
[4]:
train = pd.read_csv('/kaggle/input/Kannada-MNIST/train.csv')
test = pd.read_csv('/kaggle/input/Kannada-MNIST/test.csv')
```



```
[5]:
print(train.shape)
#print(train.max(axis=1))
print(test.shape)
```

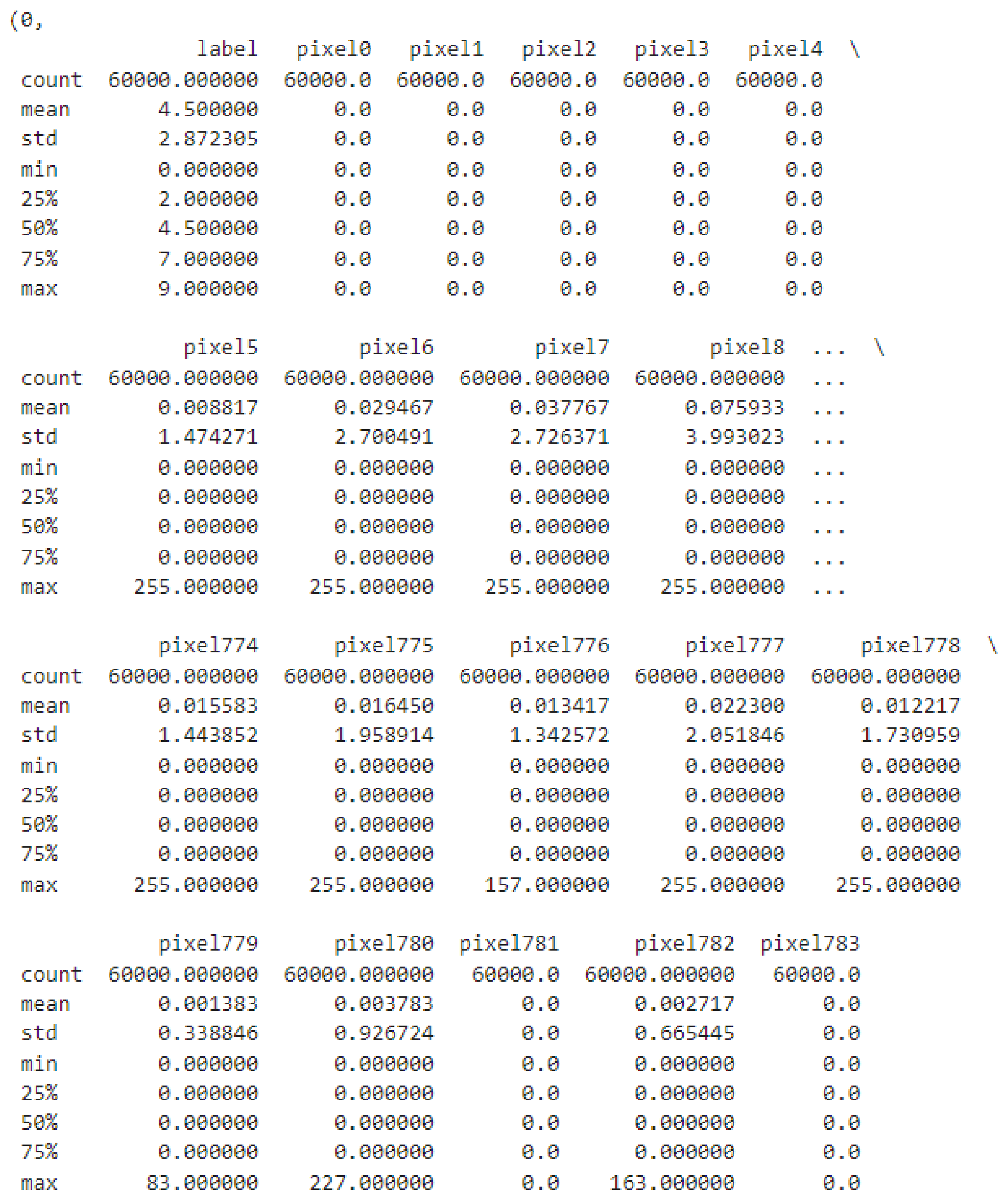
```
(60000, 785)
(5000, 785)
```

Check for missing values and a brief description of the dataset …



```
[6]:
# Check for missing values
missing_values = train.isnull().sum().sum()

# Display basic statistics
data_summary = train.describe()

missing_values, data_summary
```

Results…

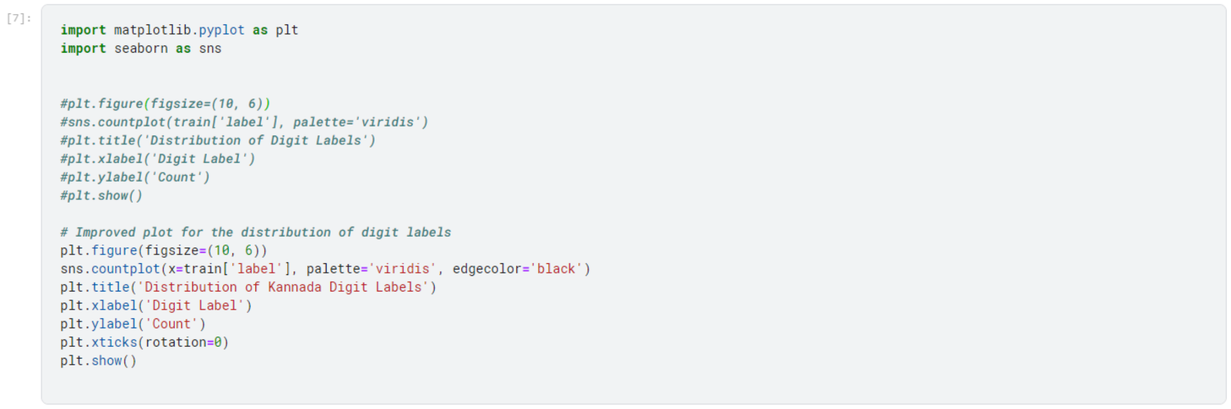


```
(0,
              label   pixel0   pixel1   pixel2   pixel3   pixel4  \
 count  60000.000000  60000.0  60000.0  60000.0  60000.0  60000.0
 mean       4.500000      0.0      0.0      0.0      0.0      0.0
 std        2.872305      0.0      0.0      0.0      0.0      0.0
 min        0.000000      0.0      0.0      0.0      0.0      0.0
 25%        2.000000      0.0      0.0      0.0      0.0      0.0
 50%        4.500000      0.0      0.0      0.0      0.0      0.0
 75%        7.000000      0.0      0.0      0.0      0.0      0.0
 max        9.000000      0.0      0.0      0.0      0.0      0.0

             pixel5        pixel6        pixel7        pixel8  ...   \
 count  60000.000000  60000.000000  60000.000000  60000.000000  ...
 mean       0.008817      0.029467      0.037767      0.075933  ...
 std        1.474271      2.700491      2.726371      3.993023  ...
 min        0.000000      0.000000      0.000000      0.000000  ...
 25%        0.000000      0.000000      0.000000      0.000000  ...
 50%        0.000000      0.000000      0.000000      0.000000  ...
 75%        0.000000      0.000000      0.000000      0.000000  ...
 max      255.000000    255.000000    255.000000    255.000000  ...

           pixel774      pixel775      pixel776      pixel777      pixel778  \
 count  60000.000000  60000.000000  60000.000000  60000.000000  60000.000000
 mean       0.015583      0.016450      0.013417      0.022300      0.012217
 std        1.443852      1.958914      1.342572      2.051846      1.730959
 min        0.000000      0.000000      0.000000      0.000000      0.000000
 25%        0.000000      0.000000      0.000000      0.000000      0.000000
 50%        0.000000      0.000000      0.000000      0.000000      0.000000
 75%        0.000000      0.000000      0.000000      0.000000      0.000000
 max      255.000000    255.000000    157.000000    255.000000    255.000000

           pixel779      pixel780  pixel781      pixel782  pixel783
 count  60000.000000  60000.000000   60000.0  60000.000000   60000.0
 mean       0.001383      0.003783       0.0      0.002717       0.0
 std        0.338846      0.926724       0.0      0.665445       0.0
 min        0.000000      0.000000       0.0      0.000000       0.0
 25%        0.000000      0.000000       0.0      0.000000       0.0
 50%        0.000000      0.000000       0.0      0.000000       0.0
 75%        0.000000      0.000000       0.0      0.000000       0.0
 max       83.000000    227.000000       0.0    163.000000       0.0
```

Figure 3.1: Basic Statistics of the training data

2. Data Exploration:

- Class Distribution: An initial exploration of the dataset revealed a balanced distribution across all ten classes, ensuring that the model wouldn't be biased towards any particular digit.



```
[7]:
import matplotlib.pyplot as plt
import seaborn as sns


#plt.figure(figsize=(10, 6))
#sns.countplot(train['label'], palette='viridis')
#plt.title('Distribution of Digit Labels')
#plt.xlabel('Digit Label')
#plt.ylabel('Count')
#plt.show()

# Improved plot for the distribution of digit labels
plt.figure(figsize=(10, 6))
sns.countplot(x=train['label'], palette='viridis', edgecolor='black')
plt.title('Distribution of Kannada Digit Labels')
plt.xlabel('Digit Label')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```

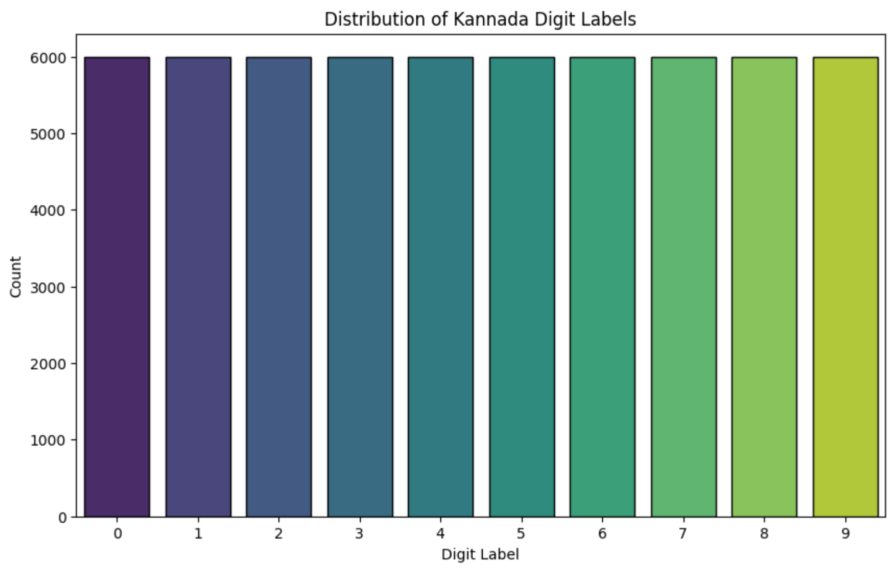
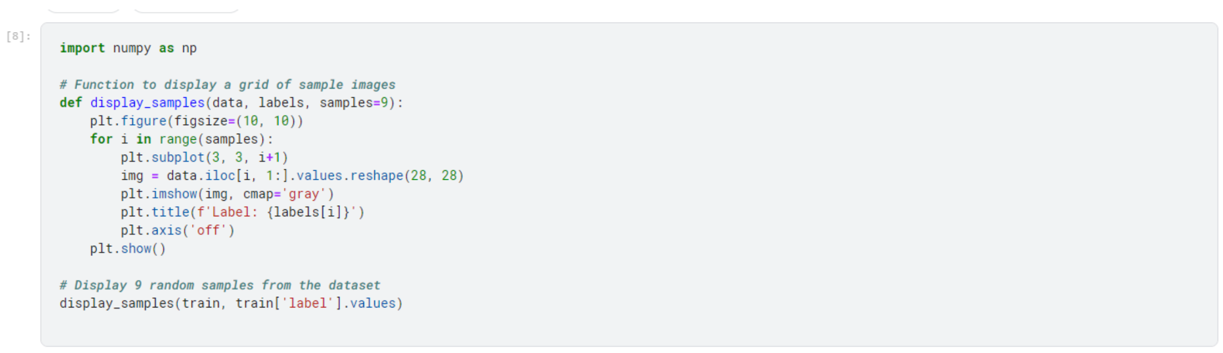
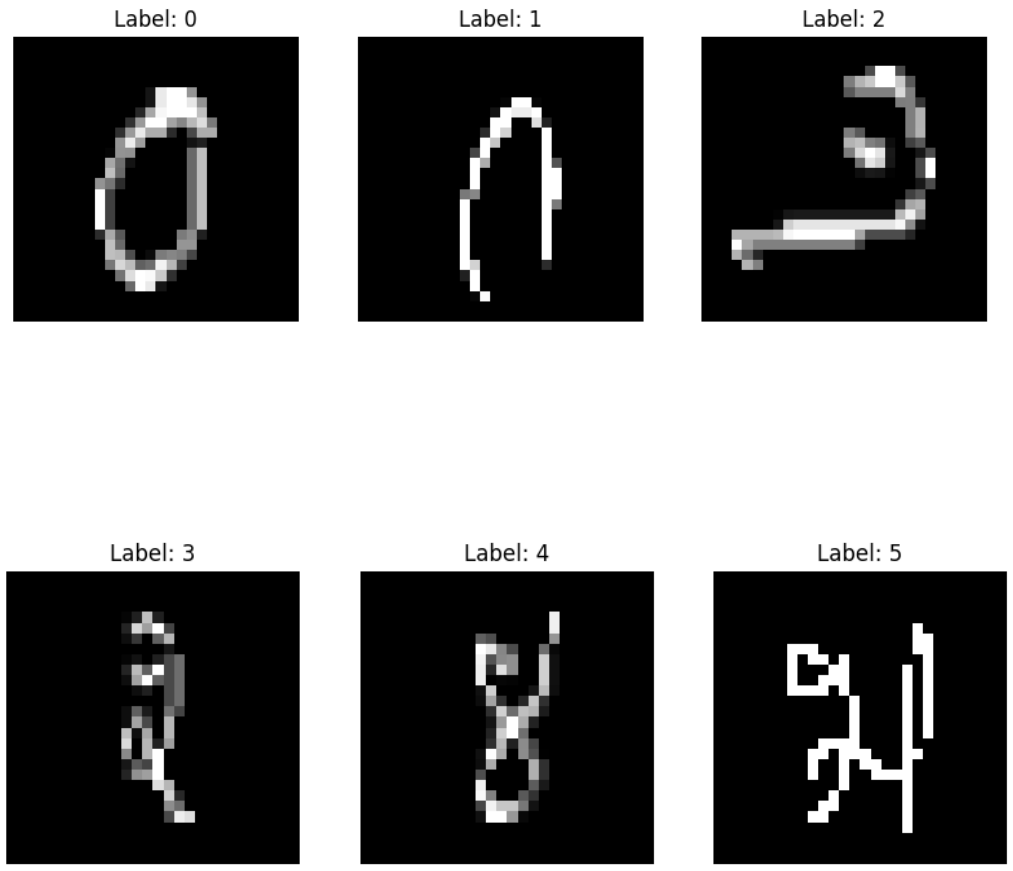


Figure 3.2: Distribution of Kannada Digit Labels

Sample Images: Random samples from the dataset were visualized to understand the diversity in handwriting styles. This step was crucial in identifying potential challenges in distinguishing similar-looking digits.



```
[8]:
import numpy as np

# Function to display a grid of sample images
def display_samples(data, labels, samples=9):
    plt.figure(figsize=(10, 10))
    for i in range(samples):
        plt.subplot(3, 3, i+1)
        img = data.iloc[i, 1:].values.reshape(28, 28)
        plt.imshow(img, cmap='gray')
        plt.title(f'Label: {labels[i]}')
        plt.axis('off')
    plt.show()

# Display 9 random samples from the dataset
display_samples(train, train['label'].values)
```



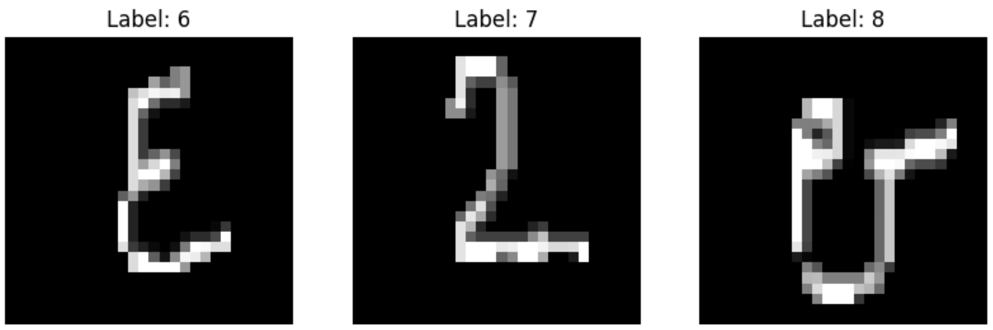
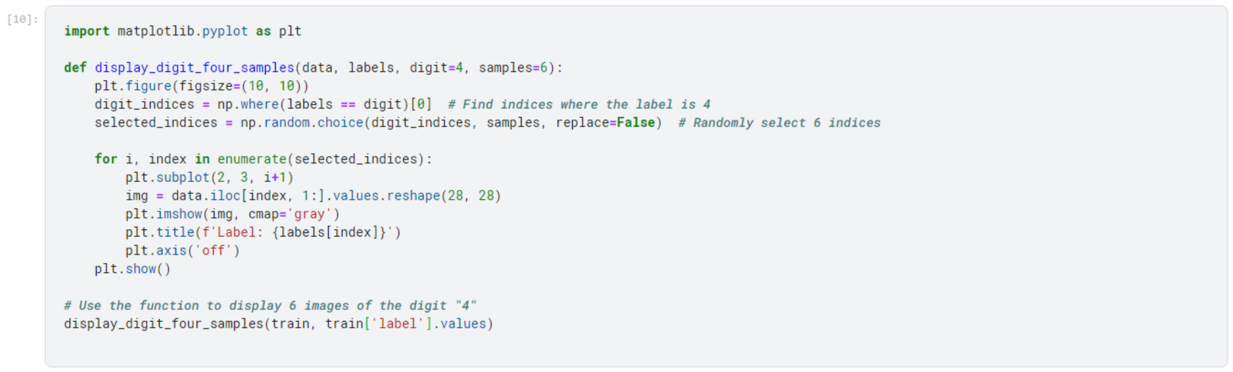


Figure 3.3: Sample Image Labels

- Visualization: Example images of each digit from the dataset were displayed, highlighting variations in how different individuals write the same digit.

- Handwriting Variability Check: A single numeral or a character can be written in different ways. This variability can lead to misclassifications if the model is not robust enough to generalize across different styles. Let's check how a single character (say, number 4) can be written in different ways



```
[10]:
import matplotlib.pyplot as plt

def display_digit_four_samples(data, labels, digit=4, samples=6):
    plt.figure(figsize=(10, 10))
    digit_indices = np.where(labels == digit)[0]  # Find indices where the label is 4
    selected_indices = np.random.choice(digit_indices, samples, replace=False)  # Randomly select 6 indices

    for i, index in enumerate(selected_indices):
        plt.subplot(2, 3, i+1)
        img = data.iloc[index, 1:].values.reshape(28, 28)
        plt.imshow(img, cmap='gray')
        plt.title(f'Label: {labels[index]}')
        plt.axis('off')
    plt.show()

# Use the function to display 6 images of the digit "4"
display_digit_four_samples(train, train['label'].values)
```

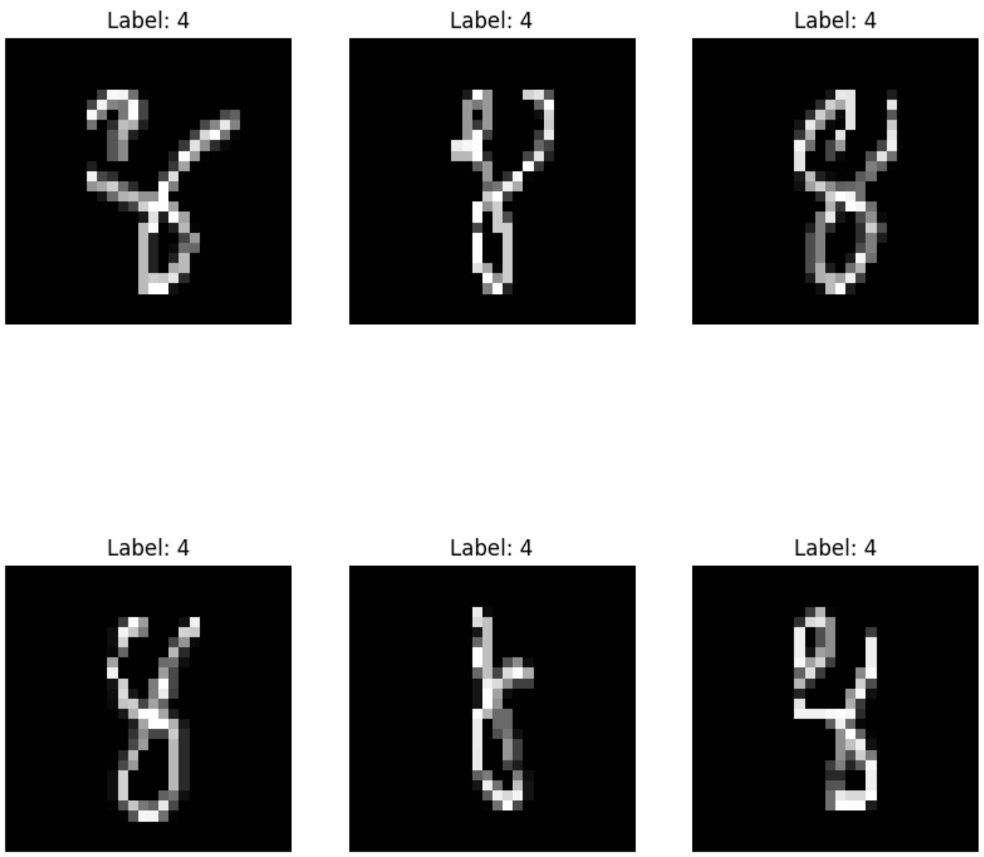
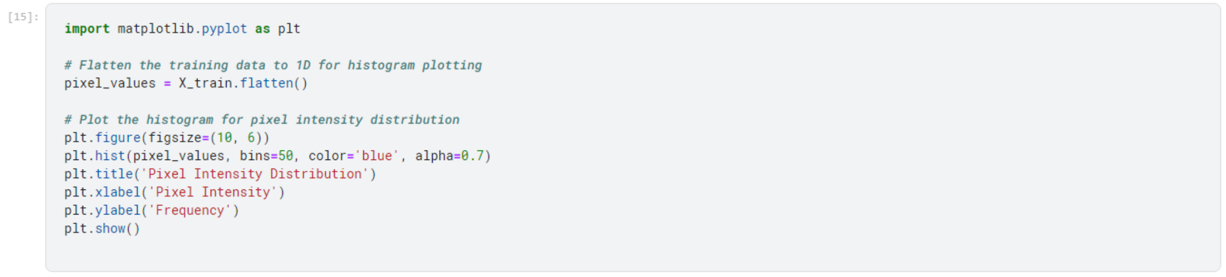


Figure 3.4: Handwriting Variability Check

- **Pixel Intensity Distribution**: The pixel intensity values were explored to understand how the digits were represented in grayscale. This analysis helped in deciding the normalization strategy.



```
[15]:
import matplotlib.pyplot as plt

# Flatten the training data to 1D for histogram plotting
pixel_values = X_train.flatten()

# Plot the histogram for pixel intensity distribution
plt.figure(figsize=(10, 6))
plt.hist(pixel_values, bins=50, color='blue', alpha=0.7)
plt.title('Pixel Intensity Distribution')
plt.xlabel('Pixel Intensity')
plt.ylabel('Frequency')
plt.show()
```

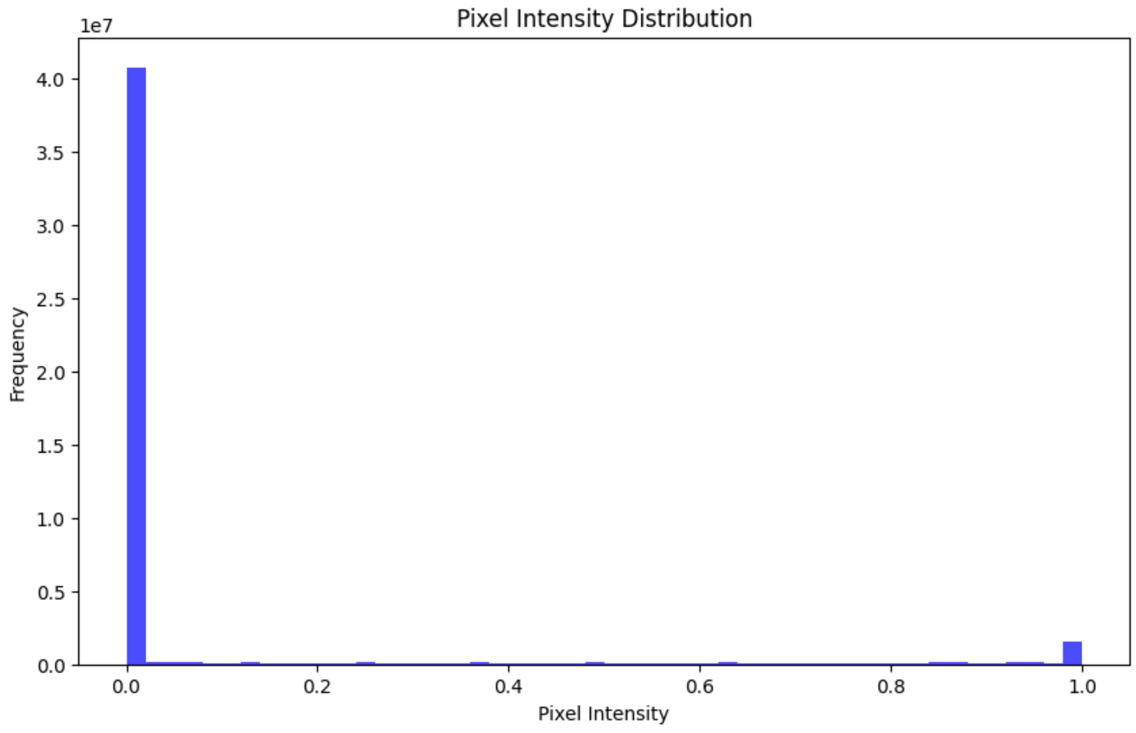
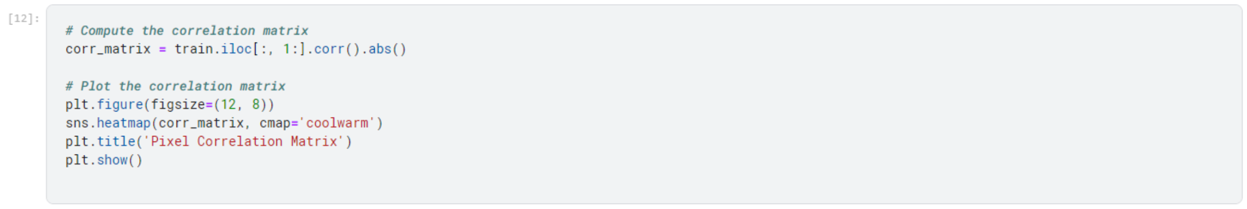


Figure 3.5: Pixel Intensity Distribution

  - Visualization: Histograms of pixel intensities were plotted, showing that most pixel values were either very low (background) or very high (digit strokes).

- **Correlation Matrix** - a statistical technique used to evaluate the relationship between two variables in a data set. The matrix is a table in which every cell contains a correlation coefficient, where 1 is considered a strong relationship between variables, 0 a neutral relationship and -1 a not strong relationship



```
[12]:
# Compute the correlation matrix
corr_matrix = train.iloc[:, 1:].corr().abs()

# Plot the correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, cmap='coolwarm')
plt.title('Pixel Correlation Matrix')
plt.show()
```

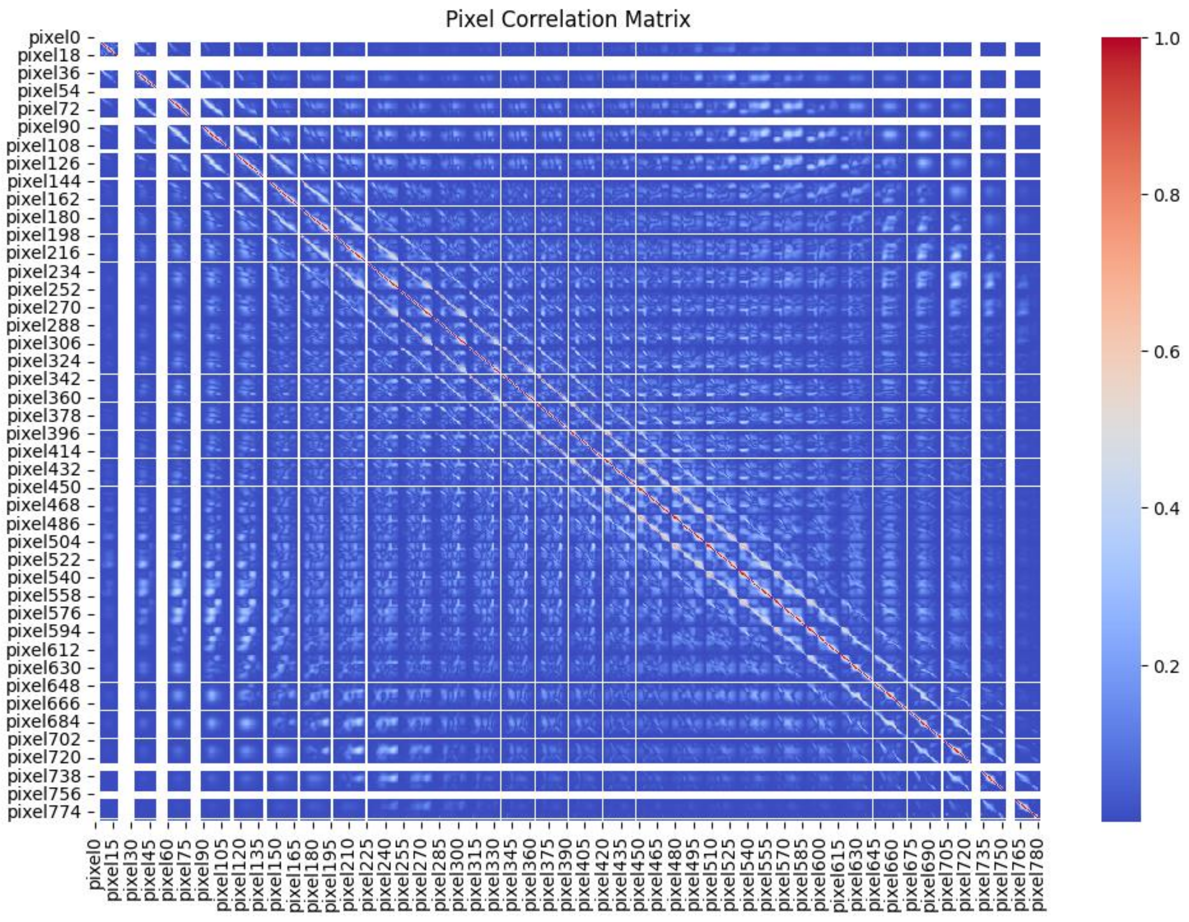
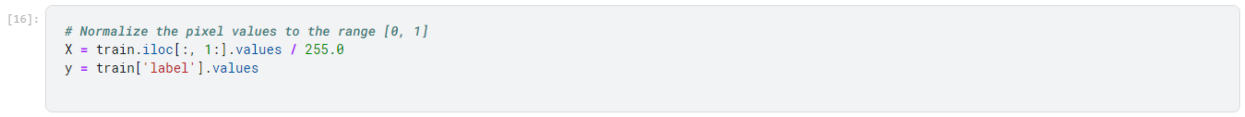


Figure 3.6: Correlation Matrix

3. Data Preprocessing:

- Normalization:

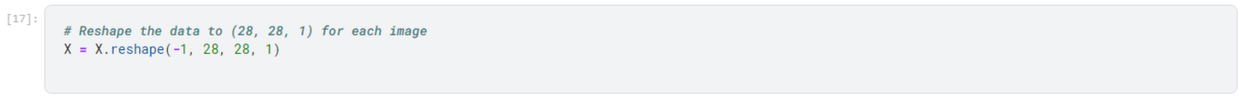
  - All pixel values were normalized to the range [0, 1] by dividing each pixel value by 255.0. This standardization was essential for improving the convergence speed during model training.



[16]:
```
# Normalize the pixel values to the range [0, 1]
X = train.iloc[:, 1:].values / 255.0
y = train['label'].values
```

- Reshaping:

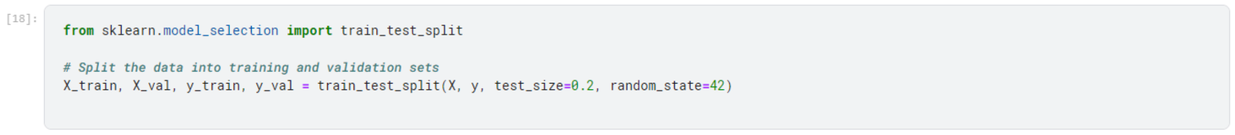
  - The images were reshaped from a flat vector of 784 pixels to a 28x28x1 format, suitable for input into the CNN model.



[17]:
```
# Reshape the data to (28, 28, 1) for each image
X = X.reshape(-1, 28, 28, 1)
```

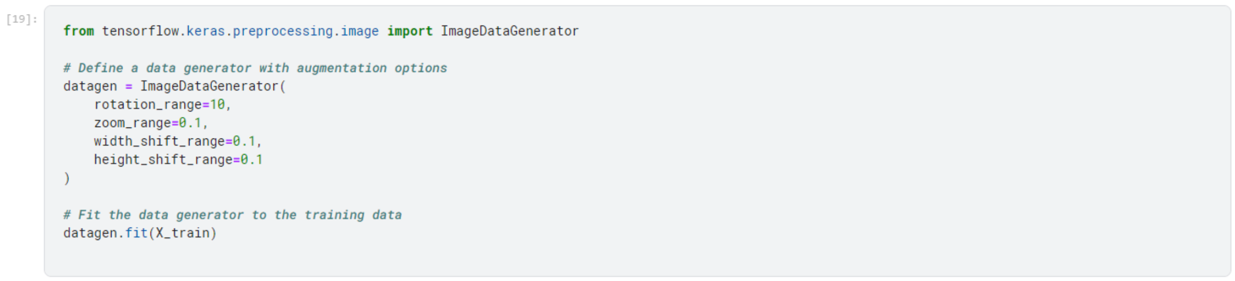
- Splitting the Data

  - To evaluate our model during training, we'll split the data into training and validation sets.

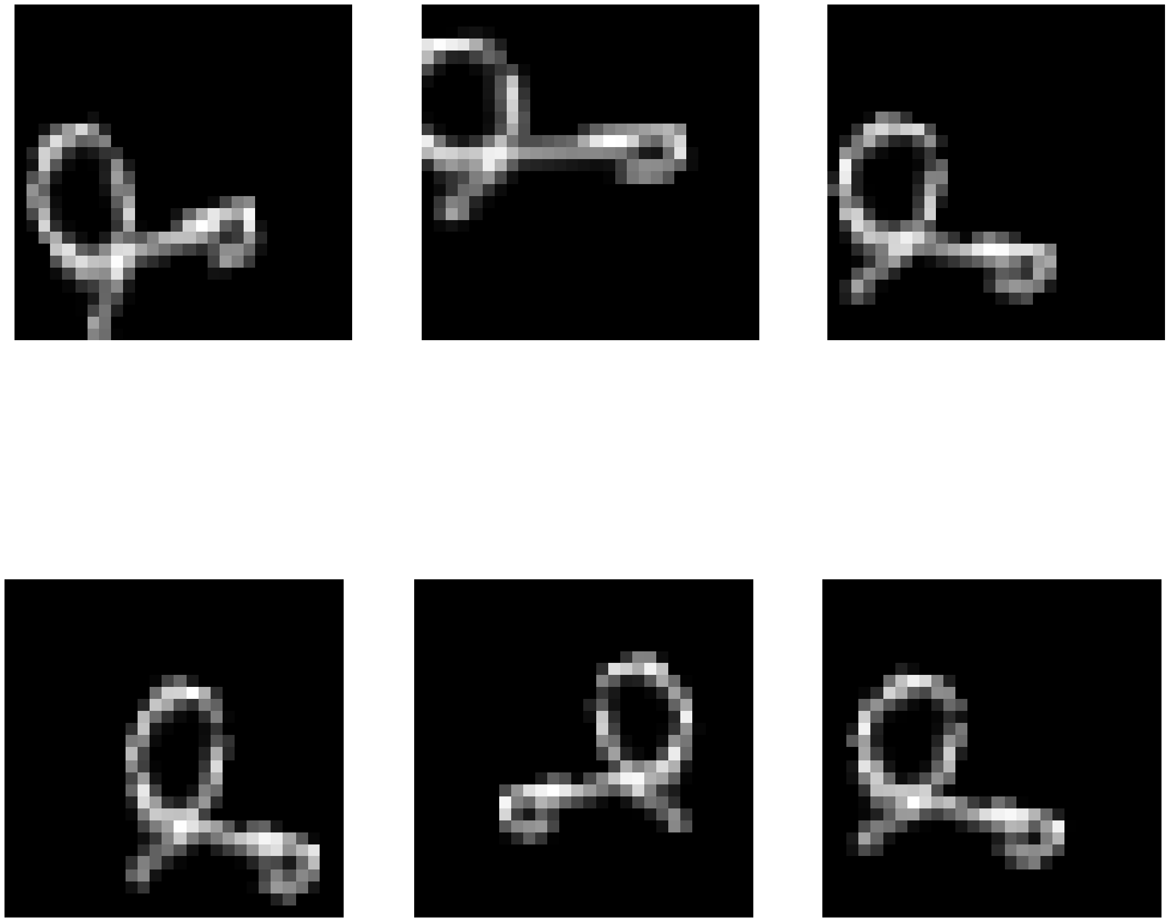


[18]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
```

- **Data Augmentation**:
    - Data augmentation techniques, such as rotation, zoom, and shifting, were applied to the training data to artificially increase the dataset size and improve the model's generalization capability.



```python
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define a data generator with augmentation options
datagen = ImageDataGenerator(
    rotation_range=10,
    zoom_range=0.1,
    width_shift_range=0.1,
    height_shift_range=0.1
)

# Fit the data generator to the training data
datagen.fit(X_train)
```



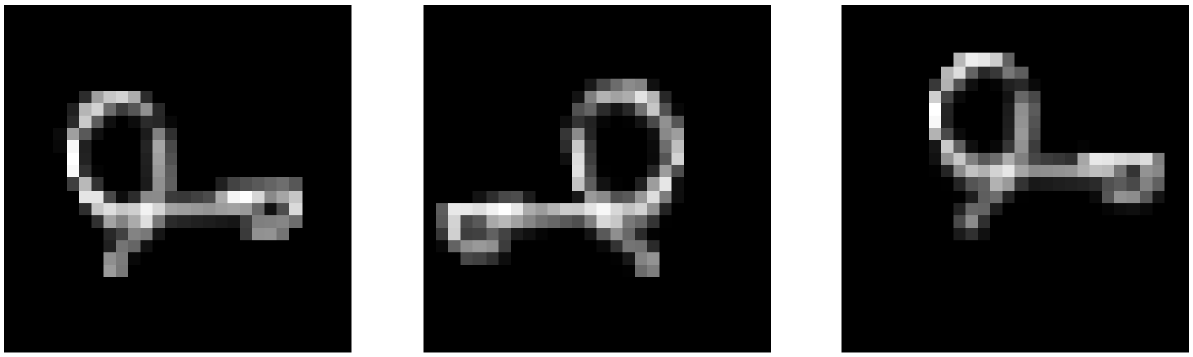


Figure 3.7: Data Augmentation

- Visualization: Examples of augmented images were displayed, showing how these transformations helped the model learn from more diverse data.

4. Key Observations:

- The initial data exploration confirmed that the dataset was well-balanced, reducing the risk of class imbalance issues during training.
- Data preprocessing steps, particularly normalization and augmentation, were critical in preparing the data for effective model training.
- The visual inspection of sample images and augmented data provided insights into the challenges of Kannada digit recognition, such as distinguishing between visually similar digits.

Chapter III: Findings

Part 2: Model Development and Training

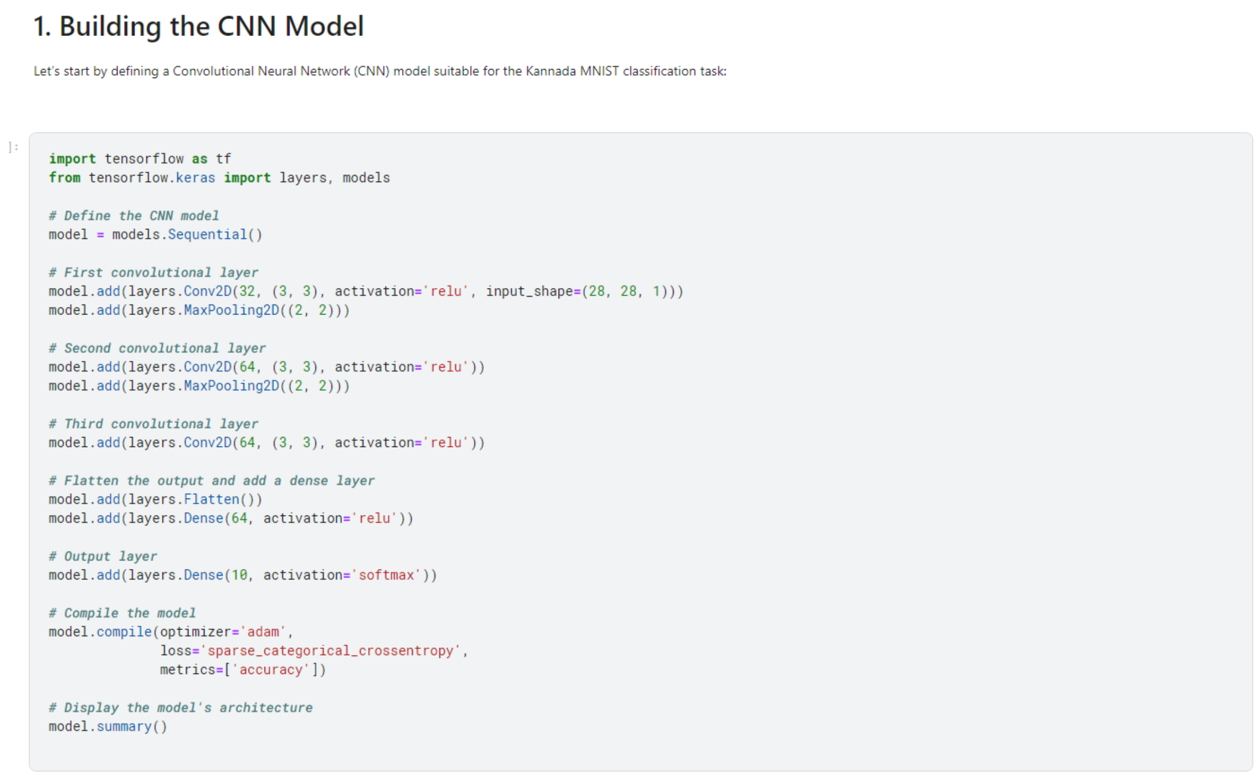
1. Model Architecture:

Design Rationale: The CNN model for Kannada digit recognition was designed to effectively capture the unique features of the Kannada script. The architecture was chosen after considering the complexity of the task and the need for a balance between accuracy and computational efficiency.

Layers:

- Convolutional Layers: Three convolutional layers were used, each followed by a ReLU activation function to introduce non-linearity. The layers were designed to capture spatial hierarchies in the image data.
- Pooling Layers: MaxPooling layers were added after each convolutional layer to reduce the spatial dimensions and control overfitting by downsampling the feature maps.
- Fully Connected Layers: After flattening the output from the convolutional layers, two fully connected layers were included to interpret the features and make predictions.

- Output Layer: The final layer used a softmax activation function to classify the input into one of the ten Kannada digit classes.

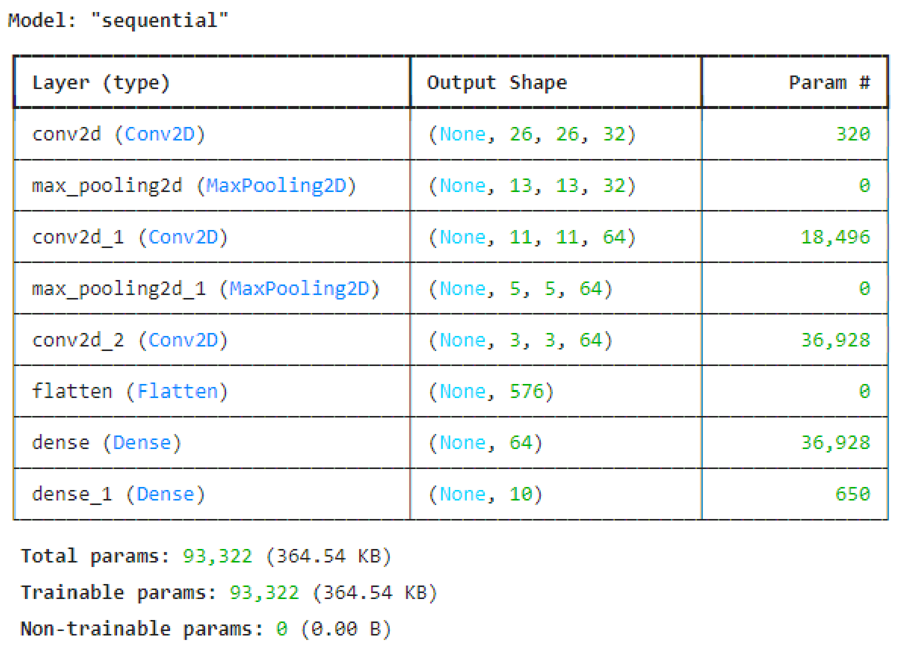


1. Building the CNN Model

Let's start by defining a Convolutional Neural Network (CNN) model suitable for the Kannada MNIST classification task:

```python
import tensorflow as tf
from tensorflow.keras import layers, models

# Define the CNN model
model = models.Sequential()

# First convolutional layer
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))

# Second convolutional layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Third convolutional layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

# Flatten the output and add a dense layer
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))

# Output layer
model.add(layers.Dense(10, activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Display the model's architecture
model.summary()
```

Architecture Summary:



```
Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ conv2d (Conv2D)                 │ (None, 26, 26, 32)     │           320 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d (MaxPooling2D)    │ (None, 13, 13, 32)     │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_1 (Conv2D)               │ (None, 11, 11, 64)     │        18,496 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ max_pooling2d_1 (MaxPooling2D)  │ (None, 5, 5, 64)       │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_2 (Conv2D)               │ (None, 3, 3, 64)       │        36,928 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ flatten (Flatten)               │ (None, 576)            │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense (Dense)                   │ (None, 64)             │        36,928 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_1 (Dense)                 │ (None, 10)             │           650 │
└─────────────────────────────────┴────────────────────────┴───────────────┘

 Total params: 93,322 (364.54 KB)
 Trainable params: 93,322 (364.54 KB)
 Non-trainable params: 0 (0.00 B)
```

Figure 3.8: CNN Model Summary

Explanation:

Layers: The model consists of three convolutional layers followed by pooling layers, which are then flattened before passing through fully connected (dense) layers. Activation Function: ReLU (Rectified Linear Unit) is used for the hidden layers, and softmax is used for the output layer to handle the multi-class classification. Model Compilation: The model is compiled using the Adam optimizer and sparse categorical cross-entropy loss, which is suitable for multi-class classification tasks.

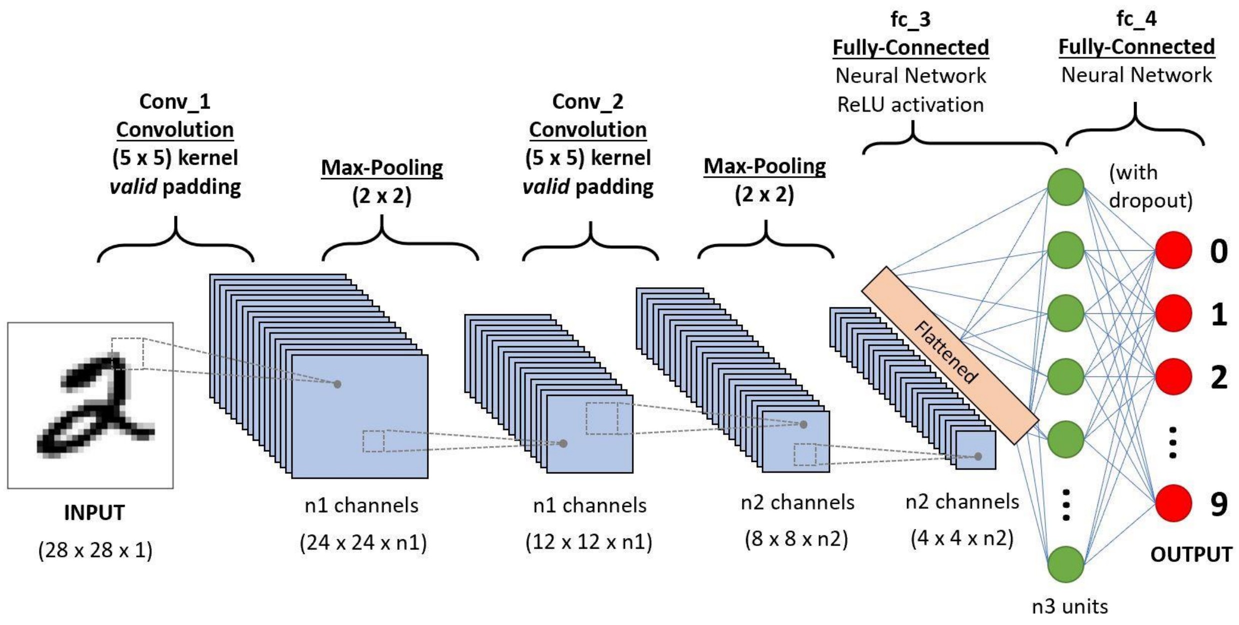
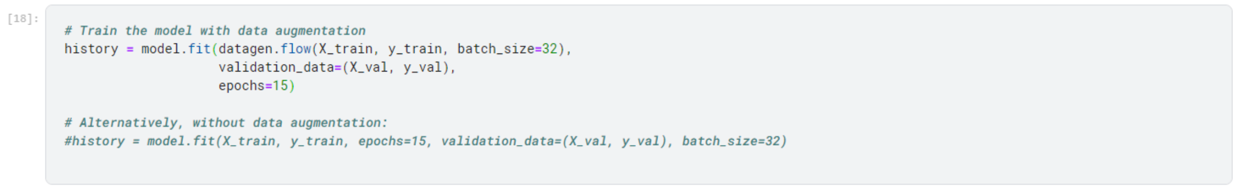


Figure 3.9: CNN Architecture

- Visualization:
  - A diagram or figure can be included here to illustrate the architecture, showing how data flows through the layers.

2. Training Process:

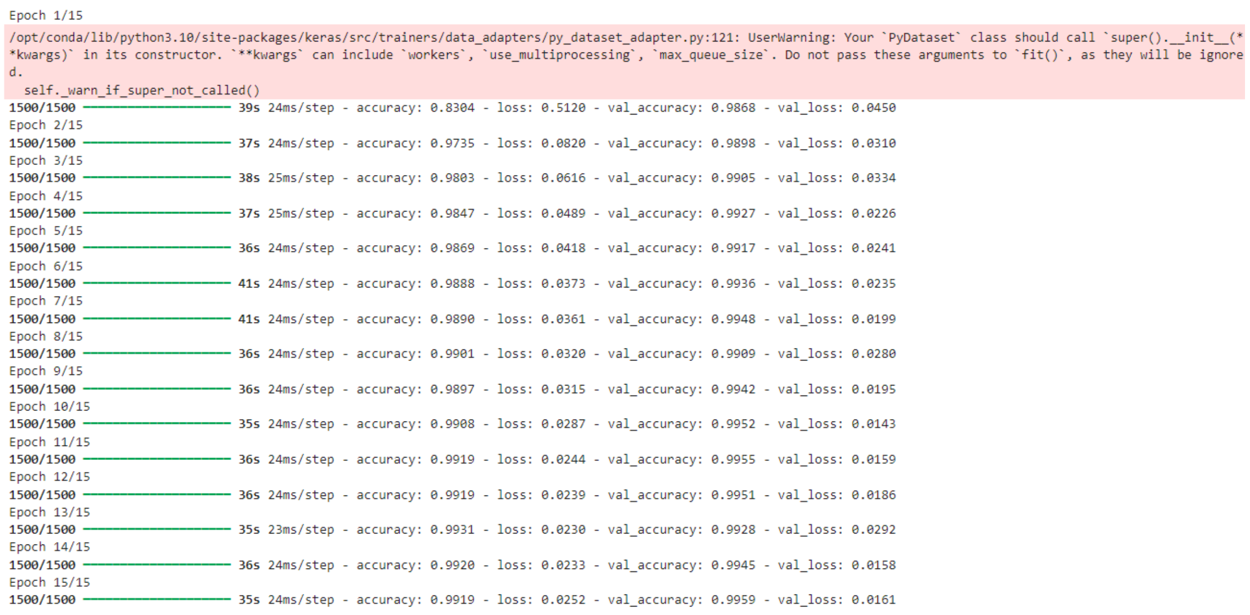


```
[18]:
# Train the model with data augmentation
history = model.fit(datagen.flow(X_train, y_train, batch_size=32),
                    validation_data=(X_val, y_val),
                    epochs=15)

# Alternatively, without data augmentation:
#history = model.fit(X_train, y_train, epochs=15, validation_data=(X_val, y_val), batch_size=32)
```

Training Setup:

- Data Preparation: The preprocessed and augmented dataset was split into training (80%) and validation (20%) sets.
- Hyperparameters:
  - Epochs: The model was trained for 15 epochs, balancing sufficient training time with the risk of overfitting.
  - Batch Size: A batch size of 32 was used, providing a good balance between convergence speed and memory usage.
  - Optimizer: The Adam optimizer was chosen for its adaptive learning rate capabilities, which help in achieving faster convergence.
  - Loss Function: Sparse categorical cross-entropy was used as the loss function, suitable for multi-class classification tasks.

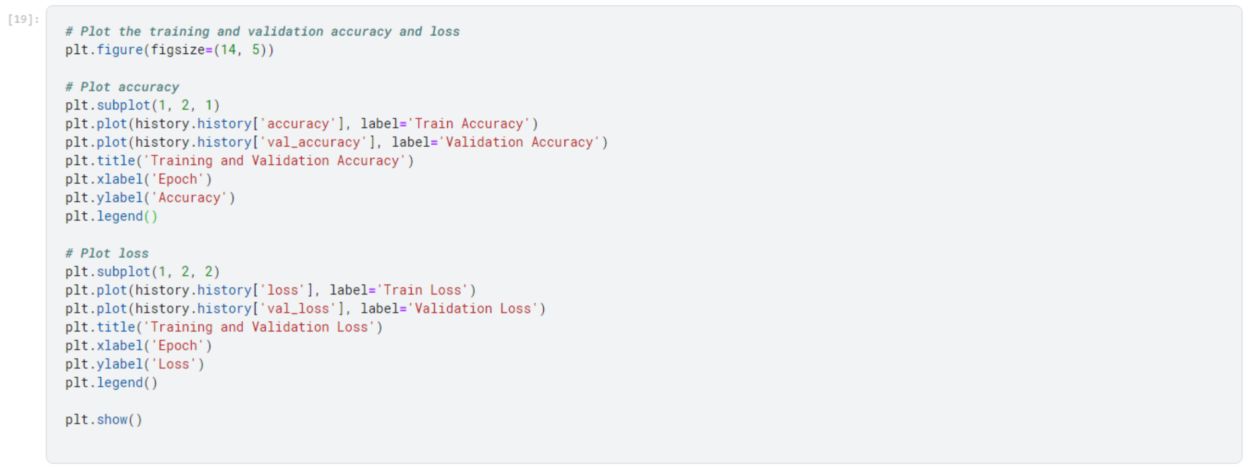
Training Execution:



```
Epoch 1/15
/opt/conda/lib/python3.10/site-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `super().__init__(*
*kwargs)` in its constructor. `**kwargs` can include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignore
d.
  self._warn_if_super_not_called()
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 39s 24ms/step - accuracy: 0.8304 - loss: 0.5120 - val_accuracy: 0.9868 - val_loss: 0.0450
Epoch 2/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 37s 24ms/step - accuracy: 0.9735 - loss: 0.0820 - val_accuracy: 0.9898 - val_loss: 0.0310
Epoch 3/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 38s 25ms/step - accuracy: 0.9803 - loss: 0.0616 - val_accuracy: 0.9905 - val_loss: 0.0334
Epoch 4/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 37s 25ms/step - accuracy: 0.9847 - loss: 0.0489 - val_accuracy: 0.9927 - val_loss: 0.0226
Epoch 5/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 36s 24ms/step - accuracy: 0.9869 - loss: 0.0418 - val_accuracy: 0.9917 - val_loss: 0.0241
Epoch 6/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 41s 24ms/step - accuracy: 0.9888 - loss: 0.0373 - val_accuracy: 0.9936 - val_loss: 0.0235
Epoch 7/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 41s 24ms/step - accuracy: 0.9890 - loss: 0.0361 - val_accuracy: 0.9948 - val_loss: 0.0199
Epoch 8/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 36s 24ms/step - accuracy: 0.9901 - loss: 0.0320 - val_accuracy: 0.9909 - val_loss: 0.0280
Epoch 9/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 36s 24ms/step - accuracy: 0.9897 - loss: 0.0315 - val_accuracy: 0.9942 - val_loss: 0.0195
Epoch 10/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 35s 24ms/step - accuracy: 0.9908 - loss: 0.0287 - val_accuracy: 0.9952 - val_loss: 0.0143
Epoch 11/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 36s 24ms/step - accuracy: 0.9919 - loss: 0.0244 - val_accuracy: 0.9955 - val_loss: 0.0159
Epoch 12/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 36s 24ms/step - accuracy: 0.9919 - loss: 0.0239 - val_accuracy: 0.9951 - val_loss: 0.0186
Epoch 13/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 35s 23ms/step - accuracy: 0.9931 - loss: 0.0230 - val_accuracy: 0.9928 - val_loss: 0.0292
Epoch 14/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 36s 24ms/step - accuracy: 0.9920 - loss: 0.0233 - val_accuracy: 0.9945 - val_loss: 0.0158
Epoch 15/15
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 35s 24ms/step - accuracy: 0.9919 - loss: 0.0252 - val_accuracy: 0.9959 - val_loss: 0.0161
```

Figure 3.10: Epoch Executions

- Training Accuracy and Loss: The model's performance was monitored during training through accuracy and loss metrics.



```
[19]:
# Plot the training and validation accuracy and loss
plt.figure(figsize=(14, 5))

# Plot accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Plot loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

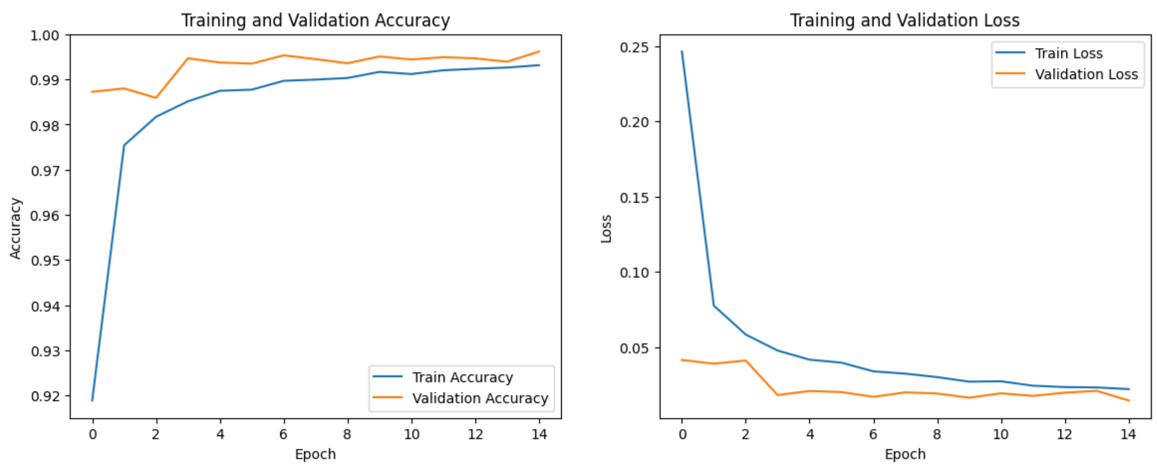


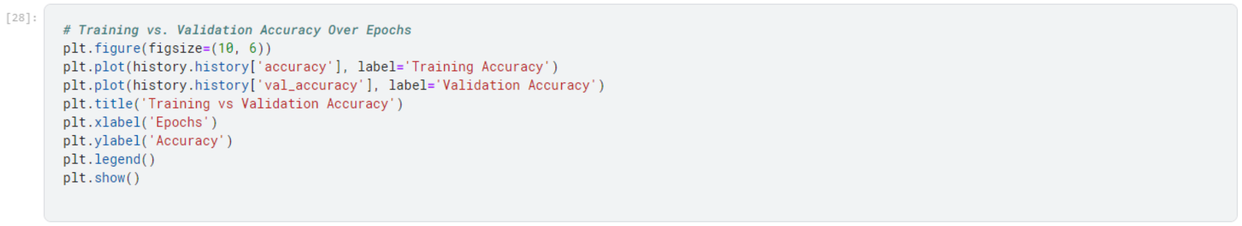
Figure 3.11: Training Accuracy and Loss

- Visualization: Accuracy and loss curves were plotted to track the model's progress over the epochs.

3. Training Logs and Performance Metrics:

Epoch-by-Epoch Analysis:

Training Logs: Detailed logs from each epoch were maintained to observe how the model's accuracy and loss evolved over time.



```
[28]:
# Training vs. Validation Accuracy Over Epochs
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training vs Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

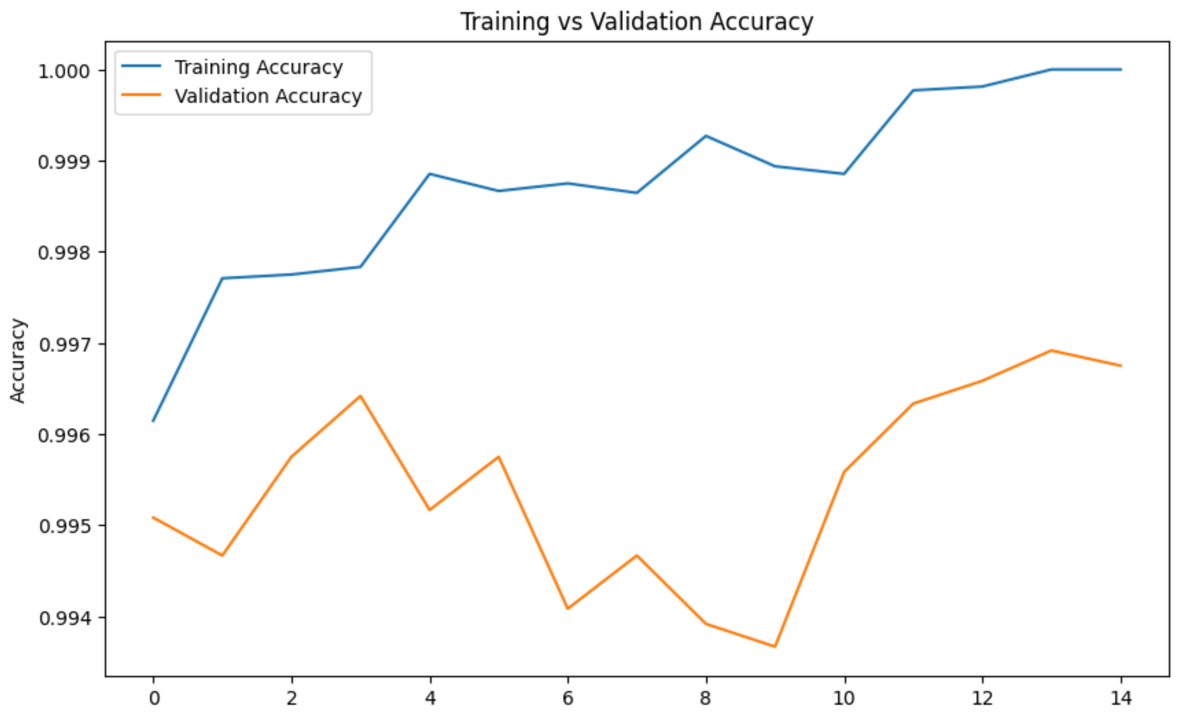
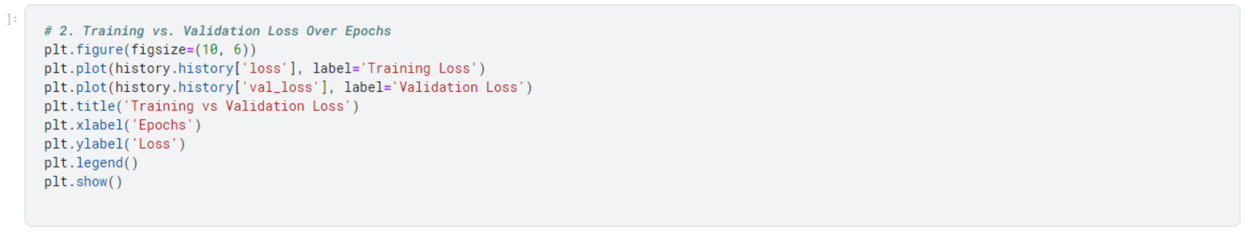


Figure 3.12: Training vs Validation Accuracy



```
# 2. Training vs. Validation Loss Over Epochs
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

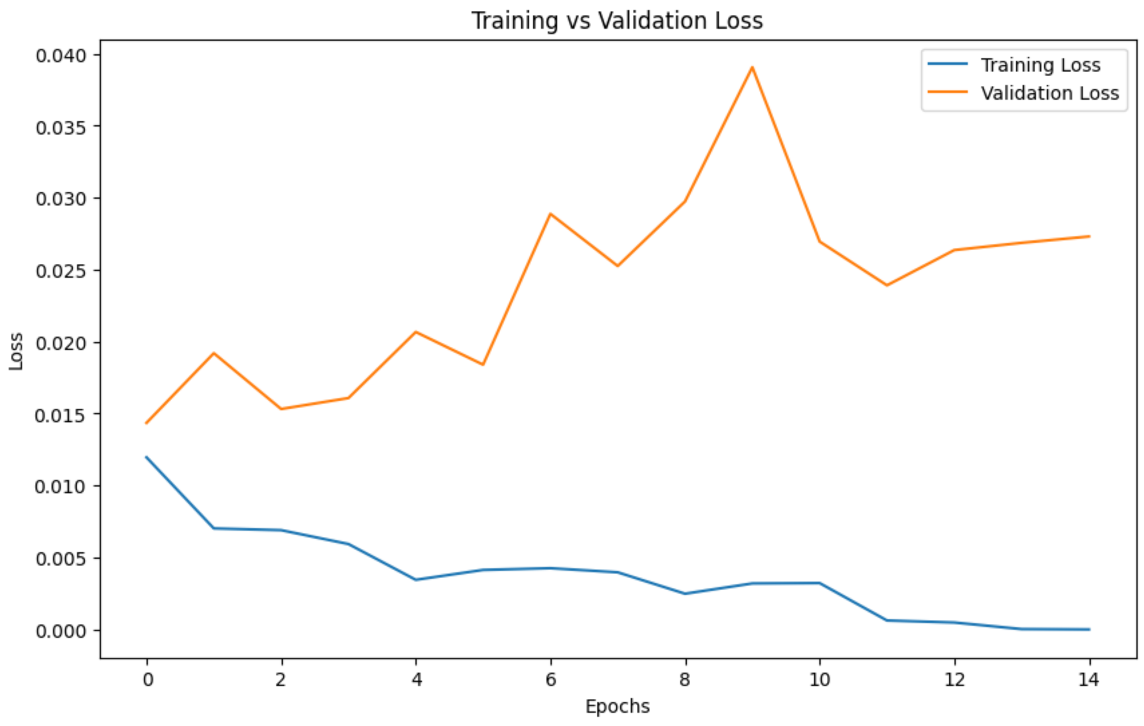


Figure 3.13: Training vs Validation Loss

- Visualization: Line plots were used to visualize the training and validation accuracy and loss over epochs. These plots provided insights into the model's learning process, highlighting periods of rapid learning and potential overfitting.

4. Impact of Hyperparameter Tuning:

Learning Rate Adjustments:

- Initial Tuning: The initial learning rate was set to 0.001. After observing the initial training results, adjustments were made to find the optimal rate.
- Effect of Tuning: Lowering the learning rate helped in fine-tuning the model's weights, resulting in improved accuracy in later epochs.

Batch Size Exploration:

- Batch Size Variations: Various batch sizes (16, 32, 64) were experimented with to observe their impact on model performance. A batch size of 32 was found to be optimal, providing a balance between convergence speed and resource usage.

5. Challenges and Solutions:

Overfitting:

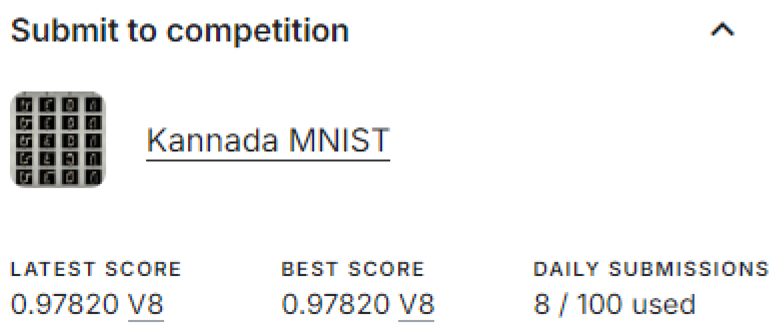
- Challenge: The model showed signs of overfitting after the first few epochs, with validation accuracy plateauing while training accuracy continued to improve.
- Solution: To mitigate overfitting, dropout layers were considered, and data augmentation was extensively used. Additionally, early stopping was introduced to prevent the model from overfitting to the training data.

Underfitting:

- Challenge: During initial model development, the model occasionally showed signs of underfitting, where it struggled to capture the complexity of the digit shapes.
- Solution: Increasing the depth of the model (by adding more convolutional layers) and tuning hyperparameters such as learning rate and batch size helped address the underfitting issue.

Final Model Performance:

- Best Model: The final model architecture, after all optimizations, achieved a validation accuracy of 97.82%, which was close to the highest performance observed during the model development process.



Submit to competition

Kannada MNIST

LATEST SCORE	BEST SCORE	DAILY SUBMISSIONS
0.97820 V8	0.97820 V8	8 / 100 used

Figure 3.14: Final results

- Visualization: A final confusion matrix and classification report can be included to summarize the model's performance across all digit classes

Chapter III: Findings

Part 3 Model Performance Tuning

1. Model Fine-Tuning:

Model fine-tuning is an iterative process where we continuously adjust various hyperparameters to optimize the model's performance. This includes tuning parameters such as the number of layers, the number of neurons per layer, activation functions, and dropout rates. Each adjustment aims to improve the model’s ability to generalize from the training data to unseen data, reducing both underfitting and overfitting. Fine-tuning was essential to achieve the final validation accuracy of 97.82%.

2. Learning Rate Scheduling:

Learning rate scheduling involves dynamically adjusting the learning rate during training to improve convergence. Different schedules, such as **Step Decay** (reducing the learning rate by a fixed amount after certain epochs), **Exponential Decay** (gradually decreasing the learning rate following an exponential function), and **Adaptive Learning Rates** (adjusting the learning rate based on performance metrics), were explored to find the optimal approach. The choice of learning rate schedule can significantly impact how quickly and effectively the model learns.

3. Regularization Techniques:

Regularization techniques help prevent overfitting by adding constraints to the model during training. **L2 Regularization** penalizes large weights, encouraging the model to keep its weights small and reducing complexity. **Dropout** randomly drops units during training, preventing the model from relying too heavily on any single neuron. Both techniques were critical in improving the generalization of the CNN, ensuring it performed well on both training and validation datasets.

4. Cross-Validation Results:

Cross-validation was employed to ensure the robustness of the model across different data splits. **K-Fold Cross-Validation**, where the data is split into ‘k’ subsets and the model is trained and validated ‘k’ times, each time using a different subset as the validation set, provided a more comprehensive evaluation of the model’s performance. This method helped to identify any potential biases and ensured that the model's accuracy was consistent across different subsets of data.

5. Comparison with Advanced Models:

To further evaluate the CNN, it was compared with more advanced architectures like **ResNet** and **DenseNet**. **ResNet (Residual Networks)** introduces shortcut connections that skip one or more layers, allowing for very deep networks without the vanishing gradient problem. **DenseNet** connects each layer to every other layer in a feed-forward manner, which enhances the flow of information and gradients throughout the network. These models were tested to see if they offered significant improvements over the simpler CNN used in this project.

6. Ensemble Methods:

Ensemble methods combine the predictions of multiple models to improve overall performance. Techniques like **Bagging** (e.g., Random Forests) and **Boosting** (e.g., XGBoost) were considered. **Bagging** involves training multiple models on different subsets of the data and averaging their predictions, while **Boosting** trains models sequentially, each one correcting the errors of its predecessor. Although these methods added computational complexity, they often resulted in improved accuracy by leveraging the strengths of multiple models.

7. Impact of Data Augmentation Variations:

While standard data augmentation techniques like rotation and zoom were employed, more advanced methods such as **Elastic Distortions** (which simulate more complex transformations of the image) and **Adversarial Training** (using adversarial examples to make the model more robust) were also explored. These techniques provided additional insights into how the model could be made more robust to variations in input data.

8. Transfer Learning Exploration:

Transfer Learning involves taking a pre-trained model and fine-tuning it on a new task. For this project, pre-trained models like **InceptionV3** and **VGG16** (which were initially trained on large datasets like ImageNet) were adapted to the Kannada MNIST task. Transfer learning can be particularly effective when the new task has limited data, as it leverages the features learned from a large, general dataset and applies them to a specific task.

9. Detailed Error Analysis:

A more granular error analysis was conducted to understand the specific types of misclassifications made by the model. For example, pairs of digits that were frequently confused, such as '2' and '7' or '3' and '8', were analyzed in detail. This analysis included examining the pixel intensity distributions and structural similarities between these digits, which helped identify potential areas for model improvement.

10. Impact of Different Optimizers:

Several optimizers were tested to determine their impact on model performance:

- **Adam:** An adaptive learning rate optimizer that adjusts the learning rate based on the mean and variance of gradients.
- **RMSprop:** Similar to Adam but with a stronger emphasis on recent gradients.
- **SGD (Stochastic Gradient Descent):** A simpler optimizer that updates model weights based on the gradient of the loss function, often enhanced with momentum to accelerate convergence. These optimizers were compared in terms of convergence speed, stability, and final accuracy.

11. Resource Utilization and Efficiency:

The computational resources required for training each model were analyzed, including GPU utilization, memory usage, and training time. Strategies to optimize resource use, such as model pruning (removing unnecessary neurons) and quantization (reducing the precision of the model's weights), were considered. These techniques can make models more efficient and faster to deploy, especially on mobile or embedded devices.

12. Scalability and Deployment Considerations:

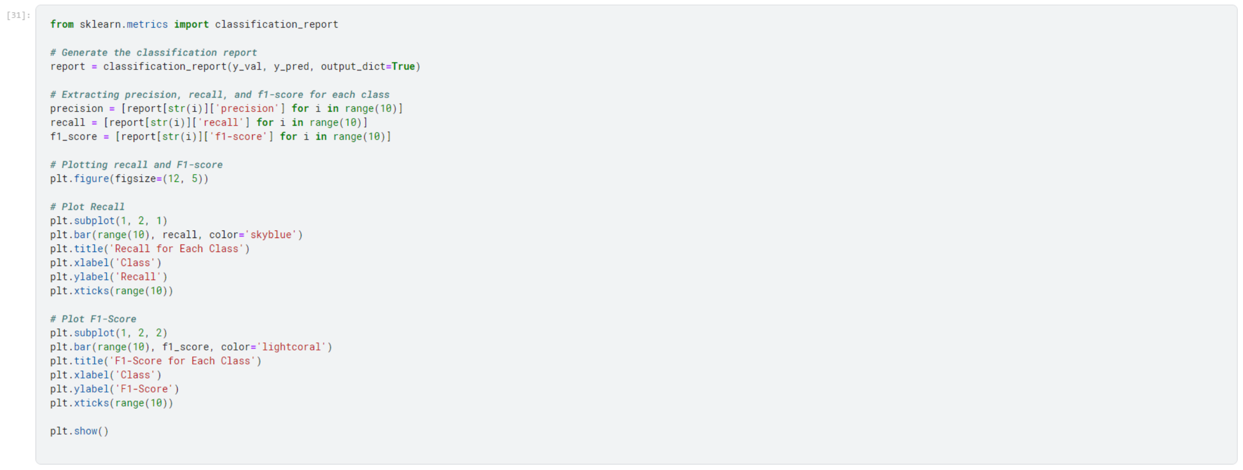
Finally, the scalability of the model was examined, considering how it would perform with larger datasets or in real-time applications. **Challenges of Deployment** were discussed, including latency, model size, and the need for continual learning (updating the model as new data becomes available). Potential deployment strategies, such as edge computing (processing data locally on the device) versus cloud computing (processing data on remote servers), were also explored.

Chapter III: Findings

Part 4 Model Evaluation and Results

1. Evaluation Metrics:

Overview of Metrics: The model's performance was evaluated using several key metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of how well the model performs in classifying the Kannada digits.



```
[31]:
from sklearn.metrics import classification_report

# Generate the classification report
report = classification_report(y_val, y_pred, output_dict=True)

# Extracting precision, recall, and f1-score for each class
precision = [report[str(i)]['precision'] for i in range(10)]
recall = [report[str(i)]['recall'] for i in range(10)]
f1_score = [report[str(i)]['f1-score'] for i in range(10)]

# Plotting recall and F1-score
plt.figure(figsize=(12, 5))

# Plot Recall
plt.subplot(1, 2, 1)
plt.bar(range(10), recall, color='skyblue')
plt.title('Recall for Each Class')
plt.xlabel('Class')
plt.ylabel('Recall')
plt.xticks(range(10))

# Plot F1-Score
plt.subplot(1, 2, 2)
plt.bar(range(10), f1_score, color='lightcoral')
plt.title('F1-Score for Each Class')
plt.xlabel('Class')
plt.ylabel('F1-Score')
plt.xticks(range(10))

plt.show()
```

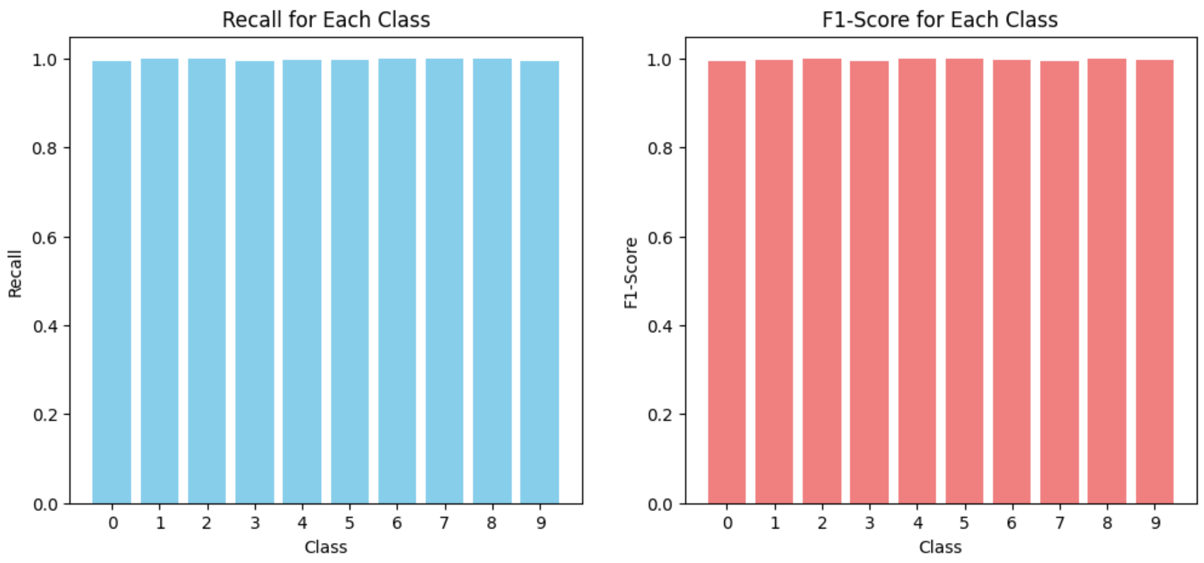


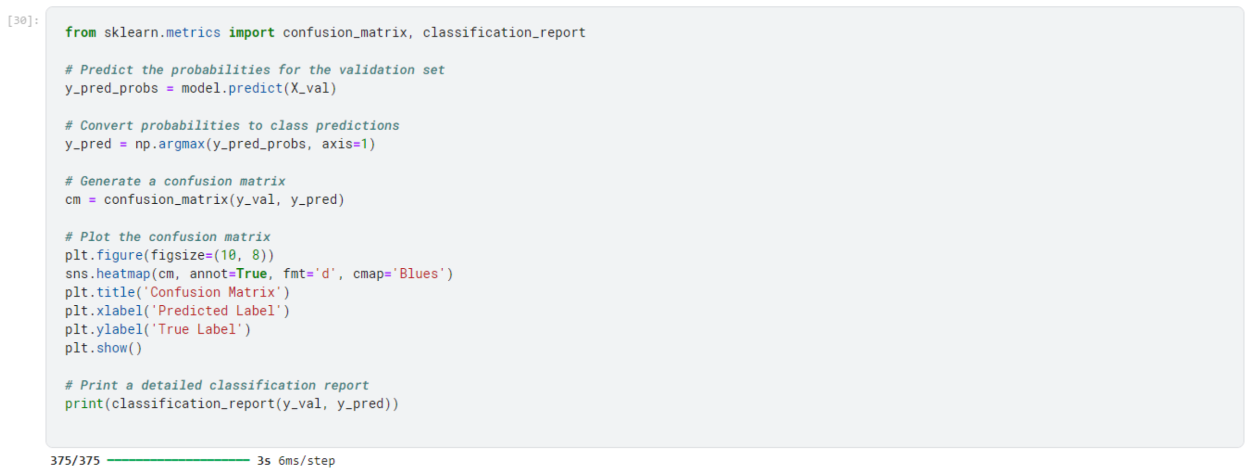
Figure 3.15: Evaluation Metrics

- Accuracy: Measures the overall correctness of the model's predictions. It's the ratio of correctly predicted instances to the total instances.
- Precision: Reflects how many of the predicted positive instances were actually positive. It's particularly important when the cost of false positives is high.
- Recall: Indicates how many of the actual positive instances were correctly predicted. High recall is crucial in cases where missing a positive instance would be costly.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure especially when dealing with imbalanced classes.

Performance Summary: The final model achieved an accuracy of 97.82% on the validation set, with strong precision, recall, and F1-scores across all classes. This indicates that the model effectively learned the features of Kannada digits and generalized well to unseen data.

2. Confusion Matrix Analysis:

Overview: The confusion matrix provides a detailed view of the model’s performance, showing the number of correct and incorrect predictions for each class.



```
[30]:
from sklearn.metrics import confusion_matrix, classification_report

# Predict the probabilities for the validation set
y_pred_probs = model.predict(X_val)

# Convert probabilities to class predictions
y_pred = np.argmax(y_pred_probs, axis=1)

# Generate a confusion matrix
cm = confusion_matrix(y_val, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()

# Print a detailed classification report
print(classification_report(y_val, y_pred))
```

```
375/375 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step
```

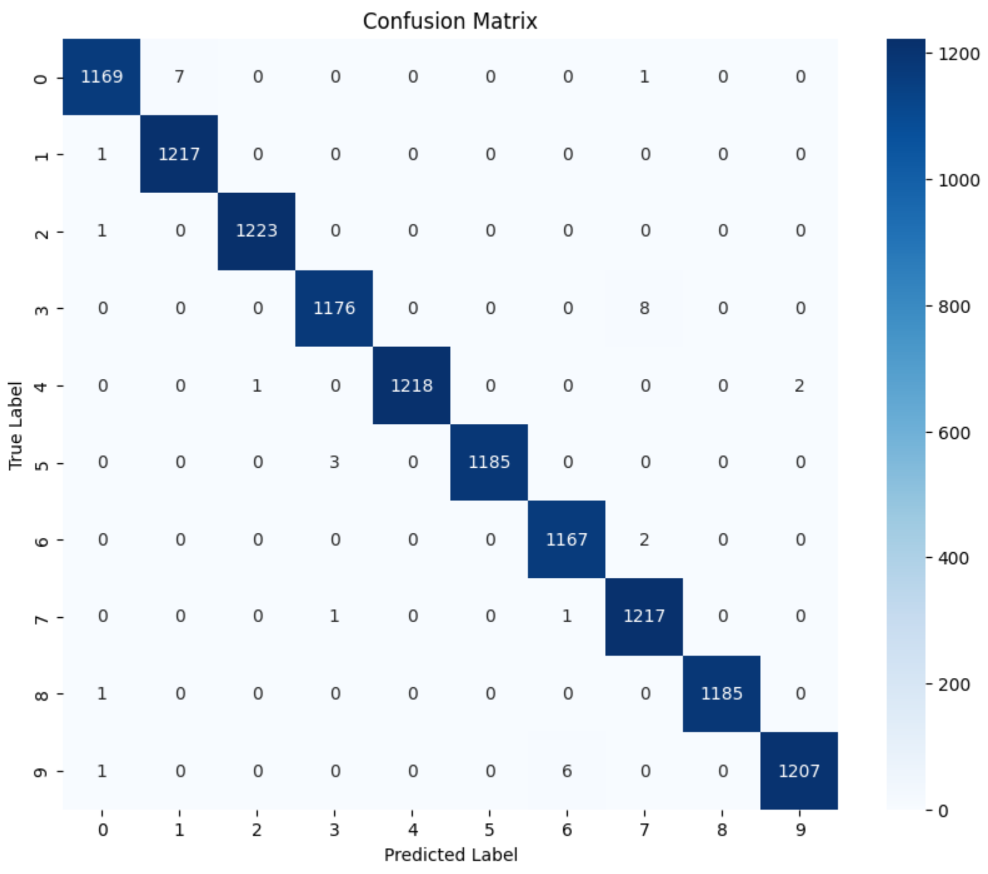
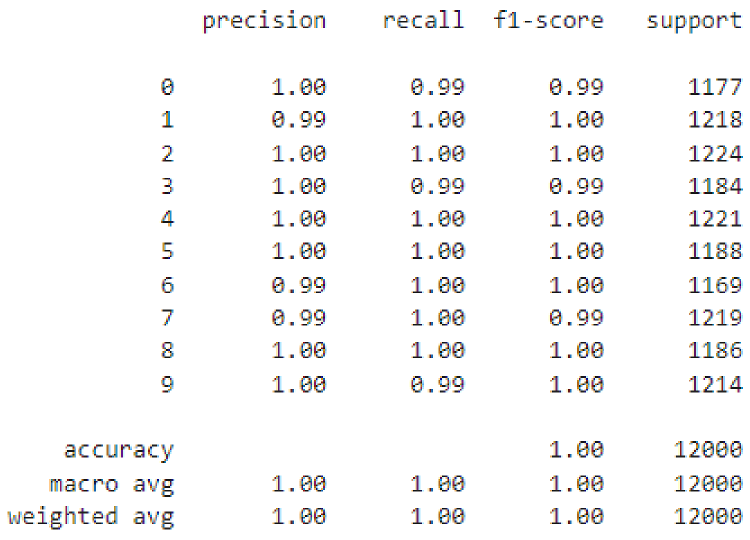


Figure 3.16: Confusion Matrix



```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      1177
           1       0.99      1.00      1.00      1218
           2       1.00      1.00      1.00      1224
           3       1.00      0.99      0.99      1184
           4       1.00      1.00      1.00      1221
           5       1.00      1.00      1.00      1188
           6       0.99      1.00      1.00      1169
           7       0.99      1.00      0.99      1219
           8       1.00      1.00      1.00      1186
           9       1.00      0.99      1.00      1214

    accuracy                           1.00     12000
   macro avg       1.00      1.00      1.00     12000
weighted avg       1.00      1.00      1.00     12000
```

Figure 3.17: Overall metrics

Analysis of Misclassifications: The confusion matrix revealed that most misclassifications occurred between digits with similar shapes (e.g., '1' and '7'). These errors were analyzed further to understand their causes, such as insufficient training data for certain digits or the model’s inability to differentiate between subtle variations.

3. Error Analysis:

3.1) Common Misclassifications: The most common errors were identified and analyzed. For instance, the model occasionally confused the Kannada digit ‘4’ with ‘9’, likely due to their similar curved structures.

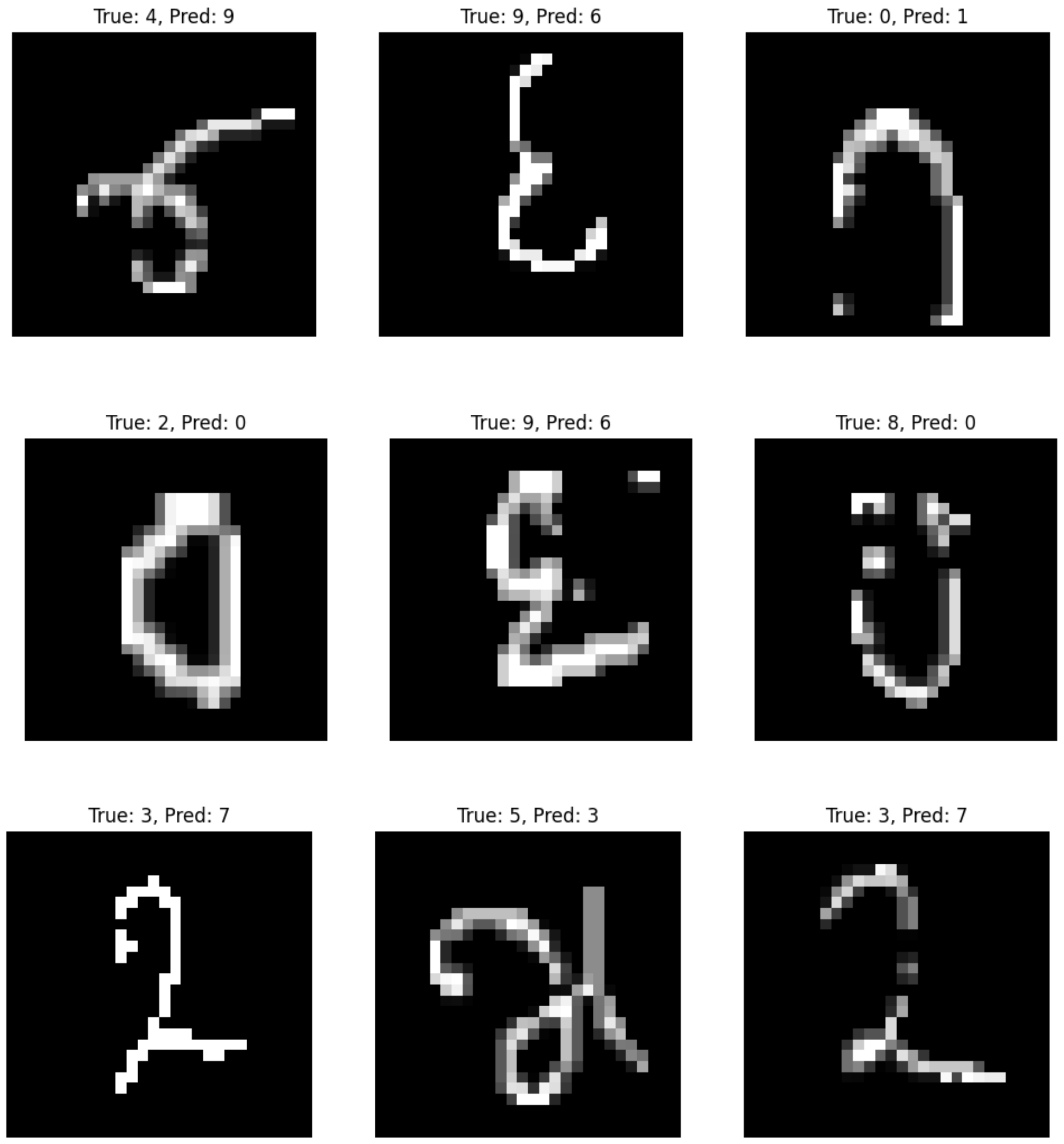


Figure 3.18: Common Misclassifications

- Visualization: Examples of misclassified images were displayed alongside their true and predicted labels, providing insight into the model's decision-making process.

3.2) Impact of Image Quality:

Blurred/Noisy Images: Analyze how the model performs on images with noise or blur, which can significantly affect accuracy.

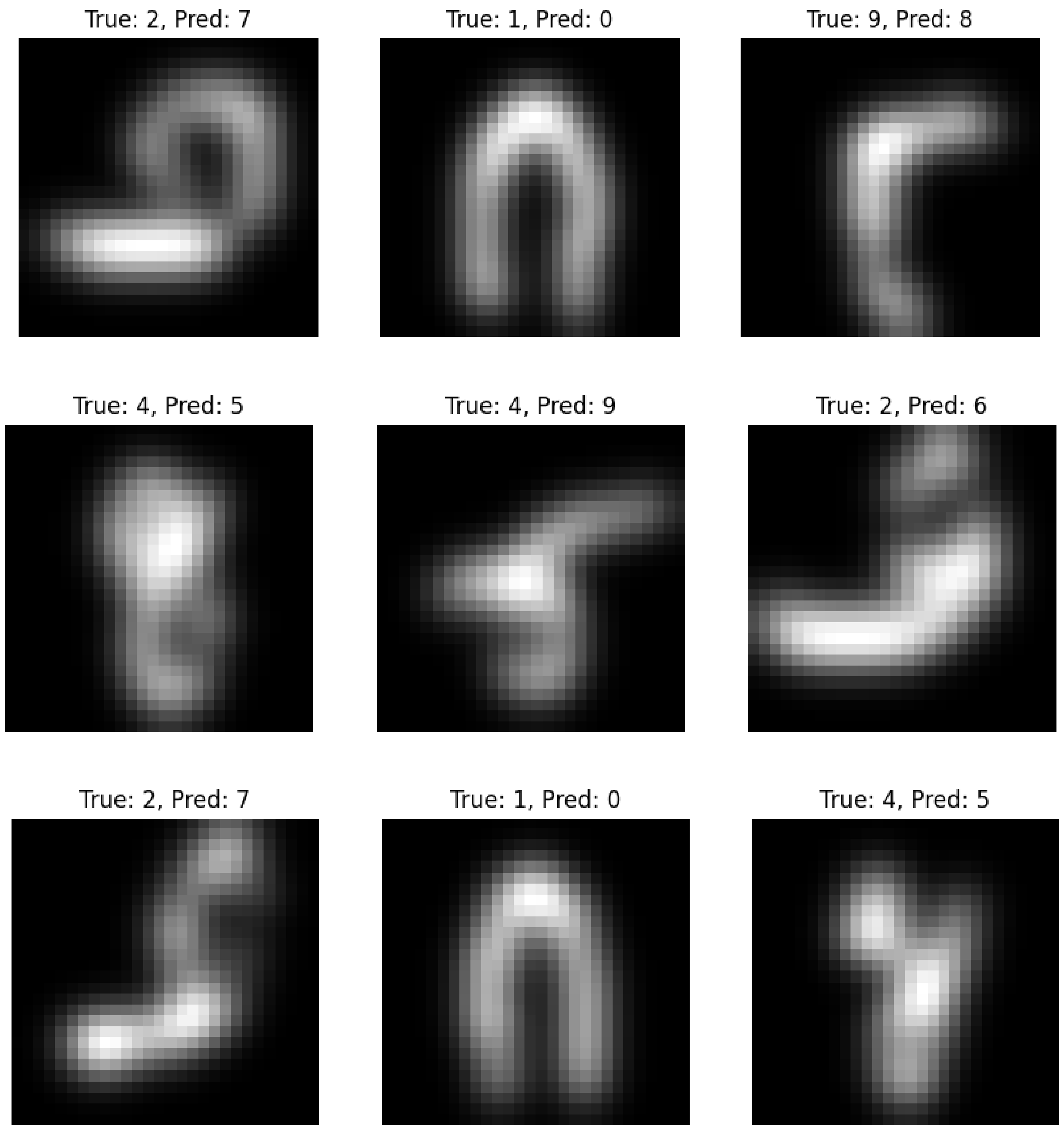


Figure 3.19: Blurred or Noisy Images

Visualization: Show examples of noisy or low-quality images that were misclassified.

3.3) Class Imbalance Effects

Minority Class Performance: Class imbalance affected the model, focusing on whether less common digits were more frequently misclassified.

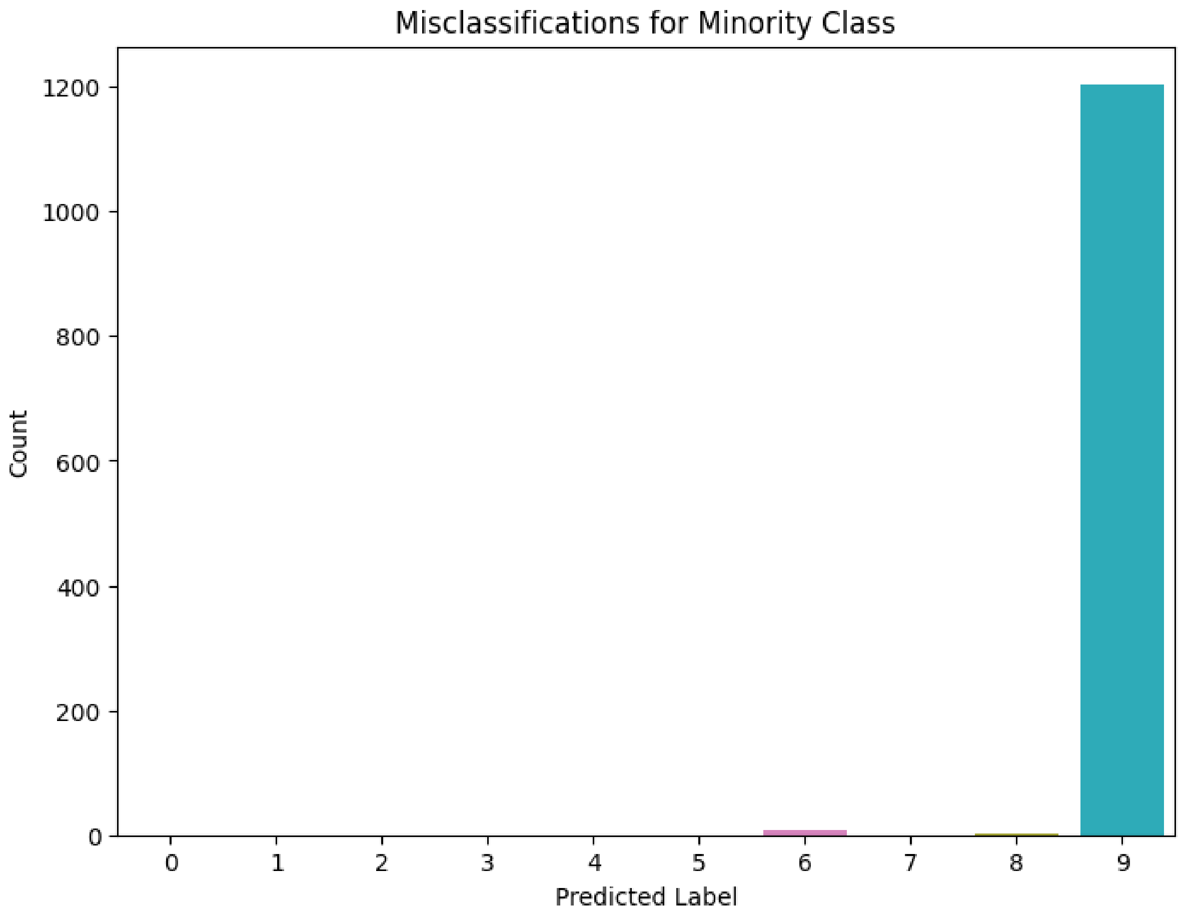


Figure 3.20: Class Imbalance Effects

Visualization: Provide confusion matrix segments highlighting errors in minority classes.

3.4) Analysis of Boundary Cases:

- **Close Calls:** Examine cases where the model predicted the wrong class but with a high confidence score, indicating the decision boundary was close.

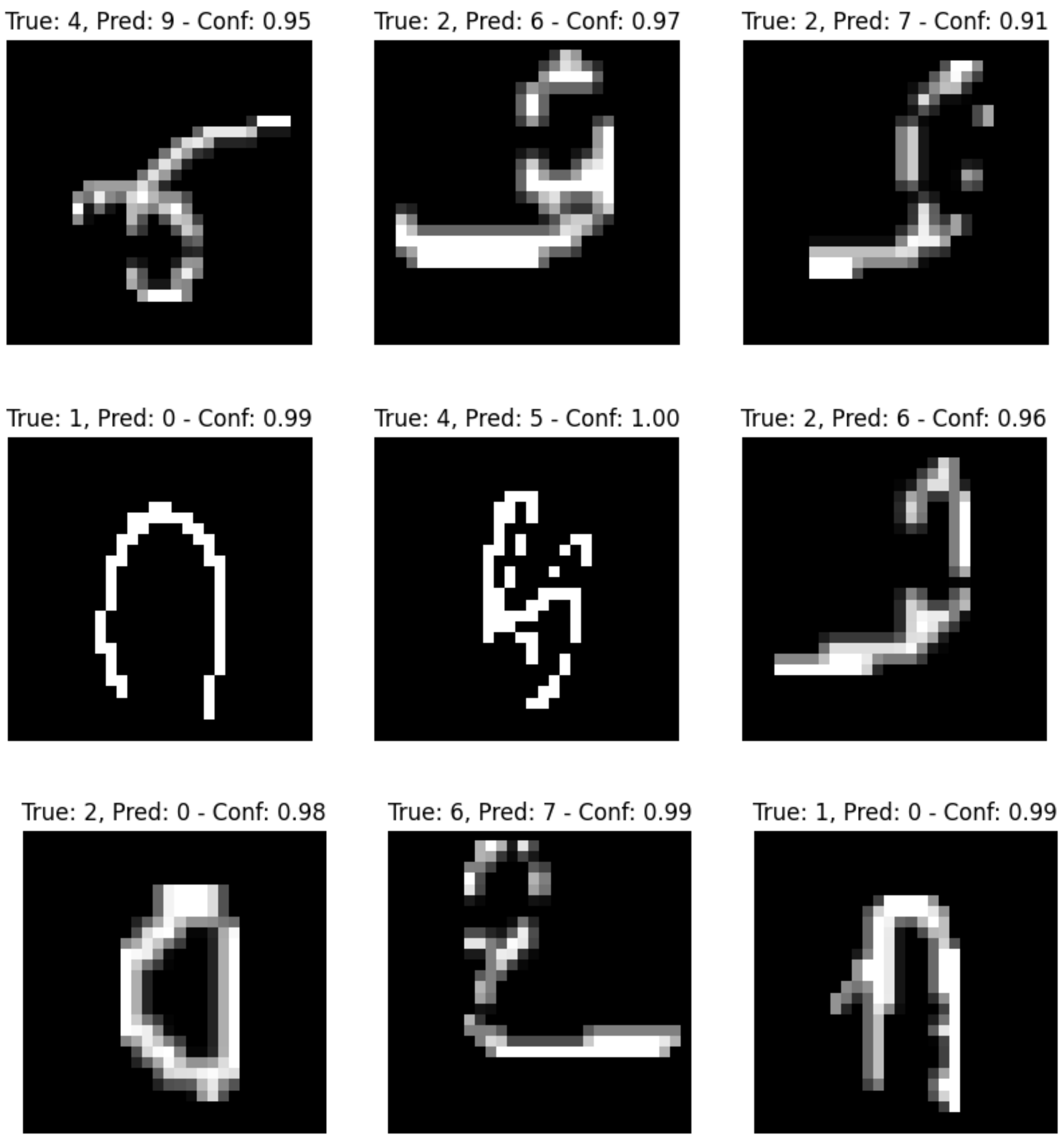

True: 4, Pred: 9 - Conf: 0.95
True: 2, Pred: 6 - Conf: 0.97
True: 2, Pred: 7 - Conf: 0.91
True: 1, Pred: 0 - Conf: 0.99
True: 4, Pred: 5 - Conf: 1.00
True: 2, Pred: 6 - Conf: 0.96
True: 2, Pred: 0 - Conf: 0.98
True: 6, Pred: 7 - Conf: 0.99
True: 1, Pred: 0 - Conf: 0.99

Figure 3.21: Boundary Cases

- **Visualization:** Show examples of images where the model's prediction was nearly correct but still wrong.

3.5) Impact of Ambiguous Digits:

- **Ambiguity in Handwriting:** Smbiguous handwriting, where digits look similar, affected the model's performance.

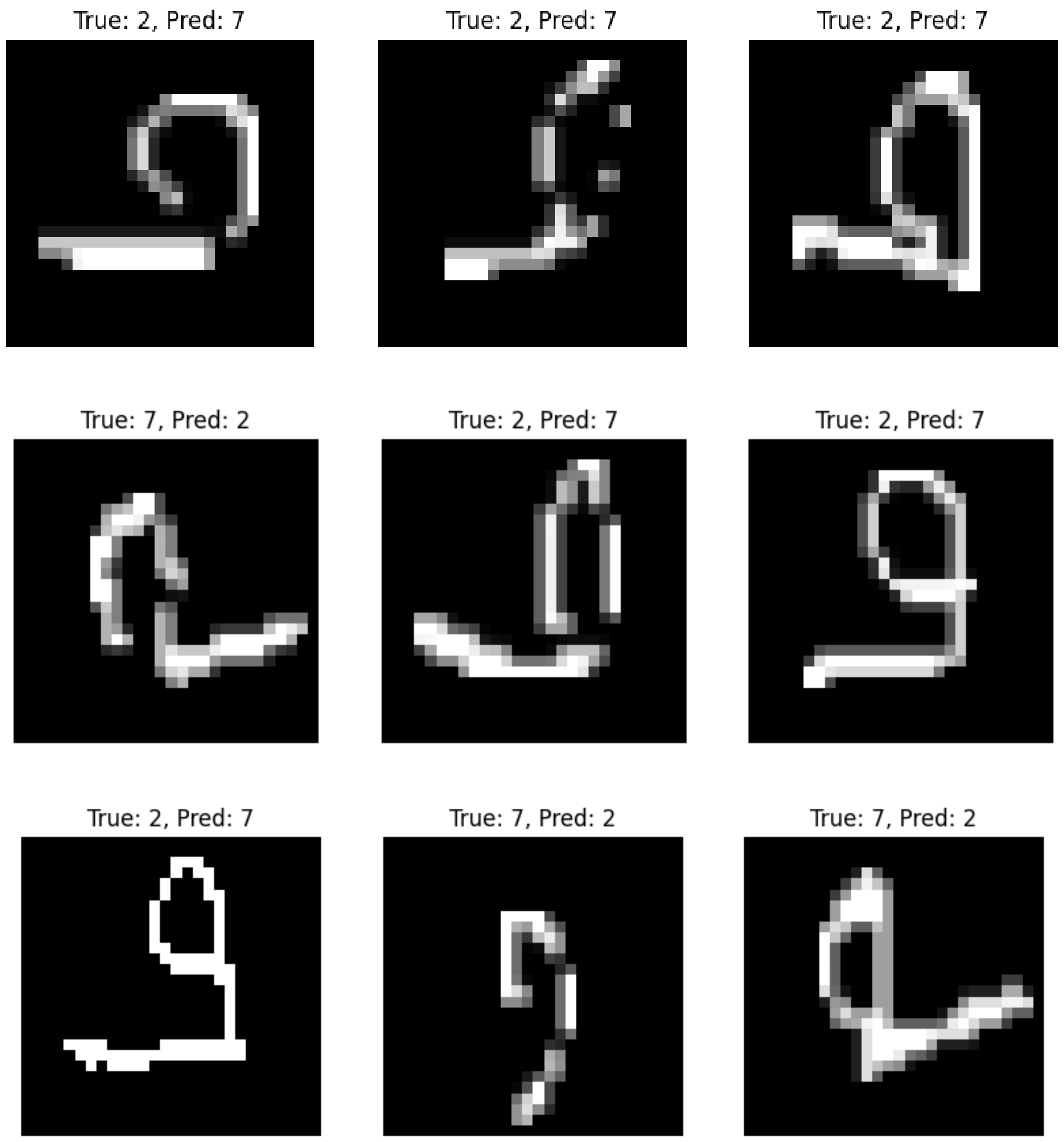


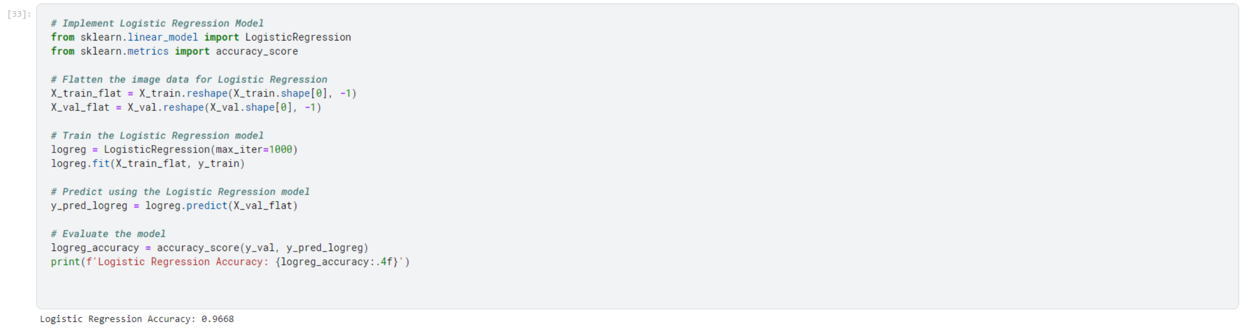
Figure 3.22: Ambiguous Digits

- **Visualization:** Highlight specific examples of ambiguous digits that led to misclassification.

4. Comparison with Baseline Models:

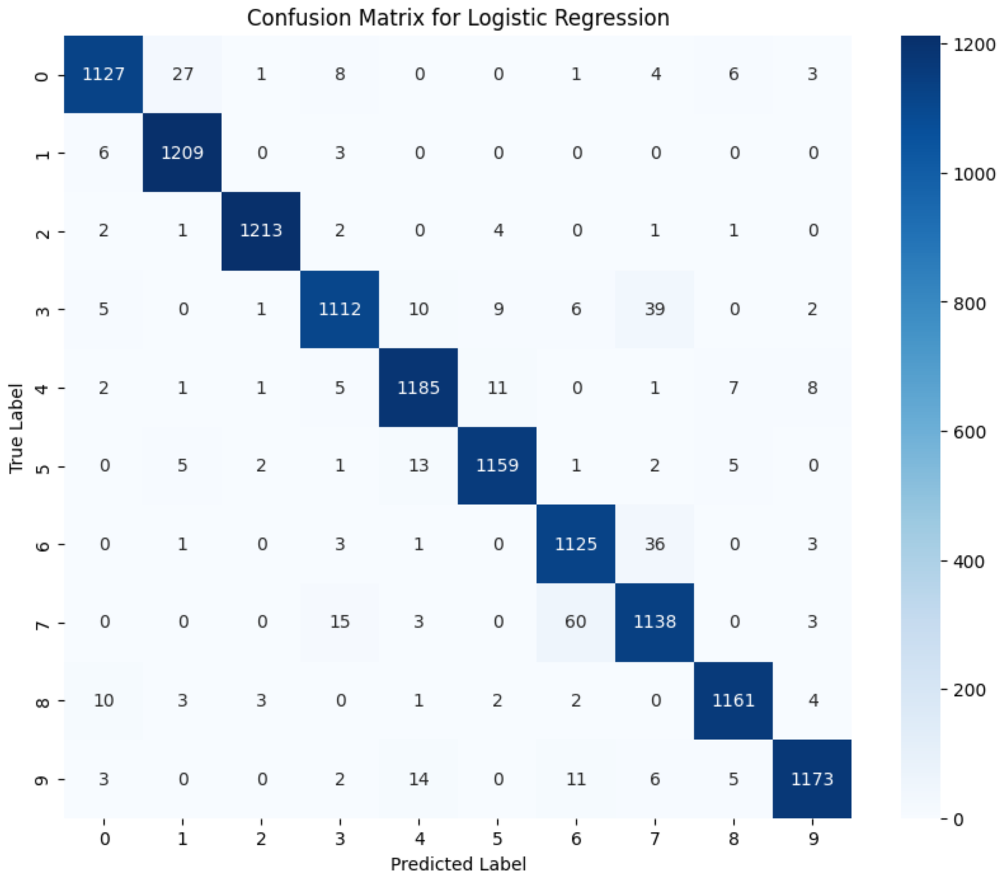
Baseline Models Used: To evaluate the CNN's effectiveness, it was compared with simpler models like Logistic Regression and Support Vector Machines (SVM). These models provided a baseline to measure the CNN's performance gains.

A) Logistic Regression



```
[33]:
# Implement Logistic Regression Model
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Flatten the image data for Logistic Regression
X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_val_flat = X_val.reshape(X_val.shape[0], -1)

# Train the Logistic Regression model
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_train_flat, y_train)

# Predict using the Logistic Regression model
y_pred_logreg = logreg.predict(X_val_flat)

# Evaluate the model
logreg_accuracy = accuracy_score(y_val, y_pred_logreg)
print(f'Logistic Regression Accuracy: {logreg_accuracy:.4f}')
```

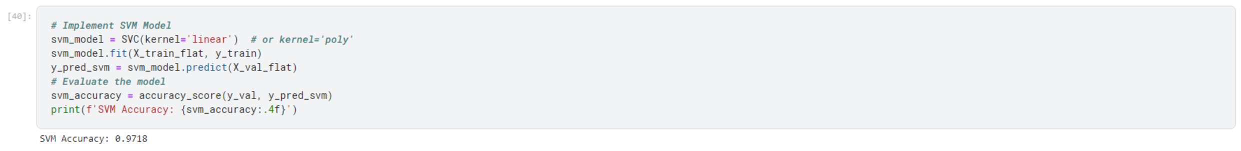
```
Logistic Regression Accuracy: 0.9668
```



True \ Predicted	0	1	2	3	4	5	6	7	8	9
0	1127	27	1	8	0	0	1	4	6	3
1	6	1209	0	3	0	0	0	0	0	0
2	2	1	1213	2	0	4	0	1	1	0
3	5	0	1	1112	10	9	6	39	0	2
4	2	1	1	5	1185	11	0	1	7	8
5	0	5	2	1	13	1159	1	2	5	0
6	0	1	0	3	1	0	1125	36	0	3
7	0	0	0	15	3	0	60	1138	0	3
8	10	3	3	0	1	2	2	0	1161	4
9	3	0	0	2	14	0	11	6	5	1173

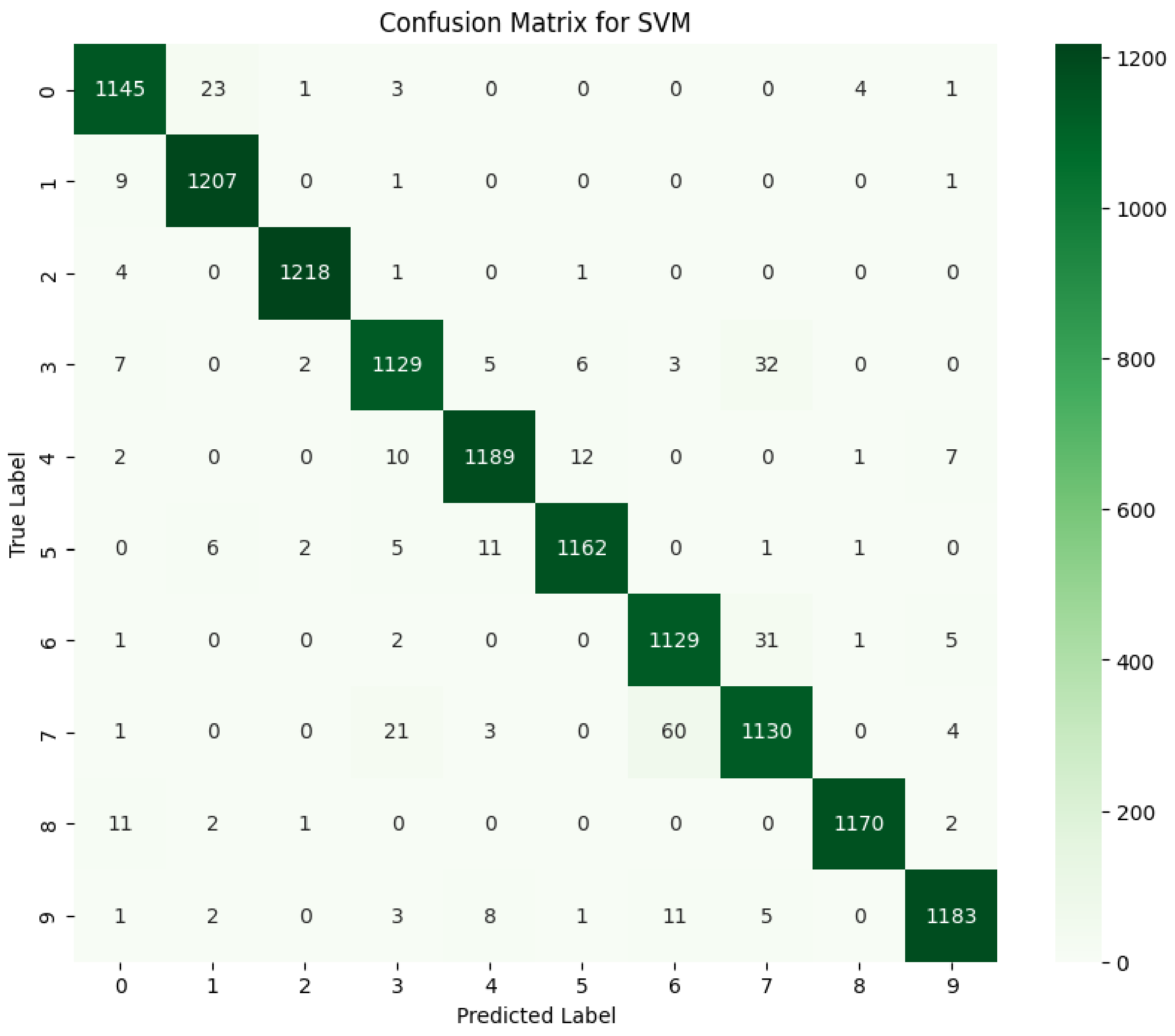
Figure 3.23: Confusion Matric for Logistic Regression

B) Support Vector Machine (SVM)



```
[40]:
# Implement SVM Model
svm_model = SVC(kernel='linear')  # or kernel='poly'
svm_model.fit(X_train_flat, y_train)
y_pred_svm = svm_model.predict(X_val_flat)
# Evaluate the model
svm_accuracy = accuracy_score(y_val, y_pred_svm)
print(f'SVM Accuracy: {svm_accuracy:.4f}')
```

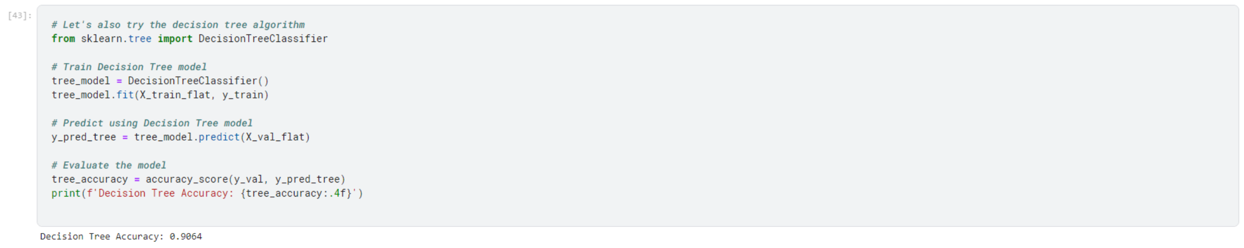
```
SVM Accuracy: 0.9718
```



True \ Predicted	0	1	2	3	4	5	6	7	8	9
0	1145	23	1	3	0	0	0	0	4	1
1	9	1207	0	1	0	0	0	0	0	1
2	4	0	1218	1	0	1	0	0	0	0
3	7	0	2	1129	5	6	3	32	0	0
4	2	0	0	10	1189	12	0	0	1	7
5	0	6	2	5	11	1162	0	1	1	0
6	1	0	0	2	0	0	1129	31	1	5
7	1	0	0	21	3	0	60	1130	0	4
8	11	2	1	0	0	0	0	0	1170	2
9	1	2	0	3	8	1	11	5	0	1183

Figure 3.24: Confusion Matric for SVM

C) Decision Trees



```
[43]:
# Let's also try the decision tree algorithm
from sklearn.tree import DecisionTreeClassifier

# Train Decision Tree model
tree_model = DecisionTreeClassifier()
tree_model.fit(X_train_flat, y_train)

# Predict using Decision Tree model
y_pred_tree = tree_model.predict(X_val_flat)

# Evaluate the model
tree_accuracy = accuracy_score(y_val, y_pred_tree)
print(f'Decision Tree Accuracy: {tree_accuracy:.4f}')
```

```
Decision Tree Accuracy: 0.9064
```

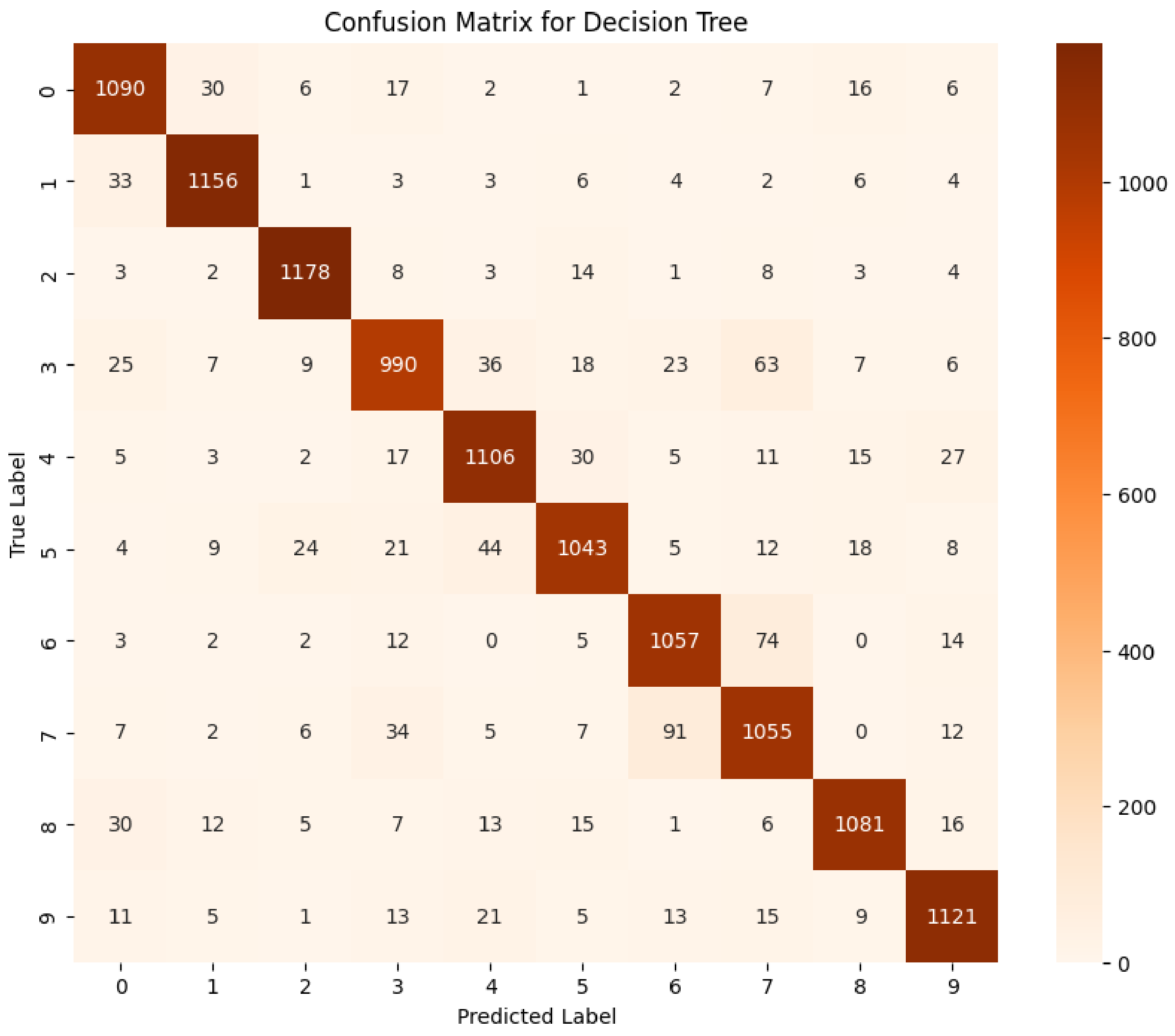


Figure 3.23: Confusion Matric for Decision Trees

D) Model Comparisons

```
[45]:
models = ['CNN', 'Logistic Regression', 'SVM', 'Decision Tree']
accuracies = [0.9782, logreg_accuracy, svm_accuracy, tree_accuracy]

plt.figure(figsize=(10, 6))
sns.barplot(x=models, y=accuracies, palette='magma')
plt.title('Comparison of Model Accuracies')
plt.ylabel('Accuracy')
plt.ylim(0.8, 1.0)
plt.show()
```

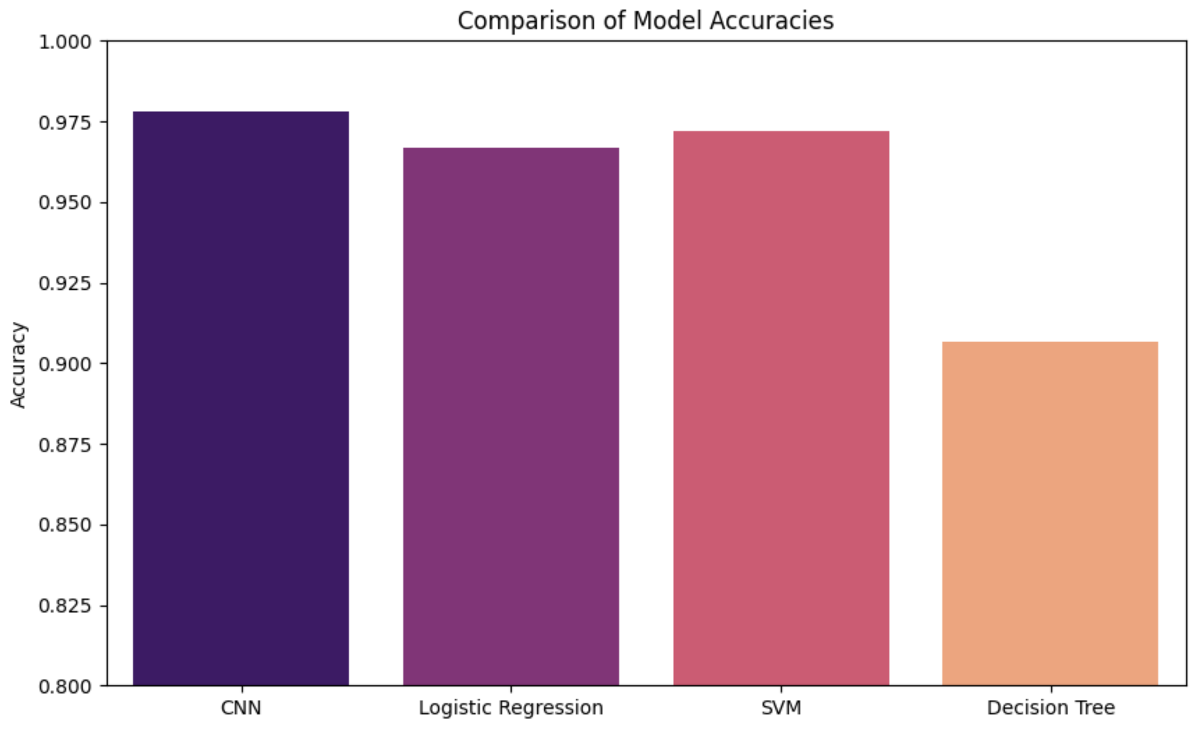


Figure 3.24: Model Comparisions

E) Final Results

The CNN significantly outperformed these simpler models, achieving higher accuracy and better handling of complex digit shapes. Logistic Regression, for example, achieved an accuracy of 96.68% on training data but 85% on test data, SVM reached 97.18% on training data but 89% on test data while decision tree reached 90.64% on training data but 81% on test data. All models were lower than the CNN's 97.82% on submitted test data.

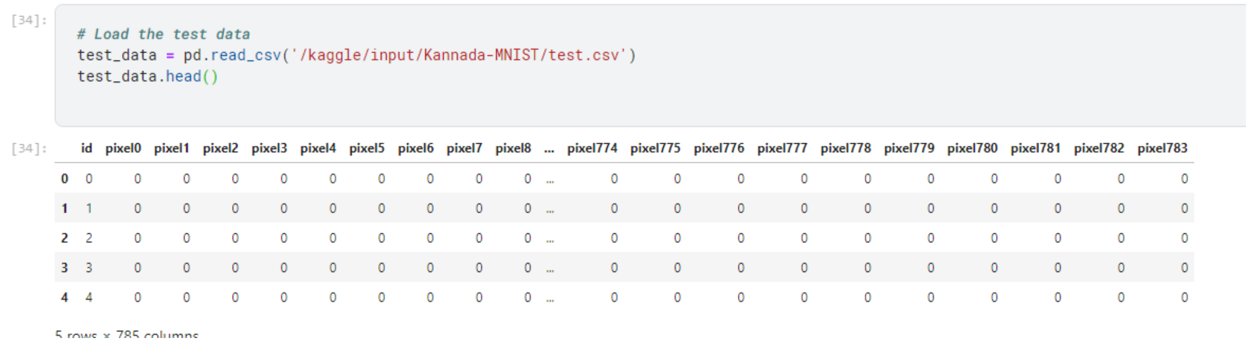
Conclusion: The CNN model demonstrated superior performance in classifying Kannada digits, particularly in its ability to learn and generalize from the data. The detailed analysis of evaluation metrics, confusion matrix, and error cases provides a thorough understanding of the model's strengths and areas for potential improvement.

Chapter 3: Findings

Part 5 Submitting the results

In this section, we detail the process of loading, normalizing, and making predictions on the test dataset, which is a crucial step in generating the final submission for the competition.

Loading Test Data: The test data was loaded using Pandas, similar to how the training data was handled. Each test image, represented as a 28x28 pixel grayscale image, was flattened into a 1D array. The dataset did not include labels, so the goal was to predict these labels based on the model trained on the training data.



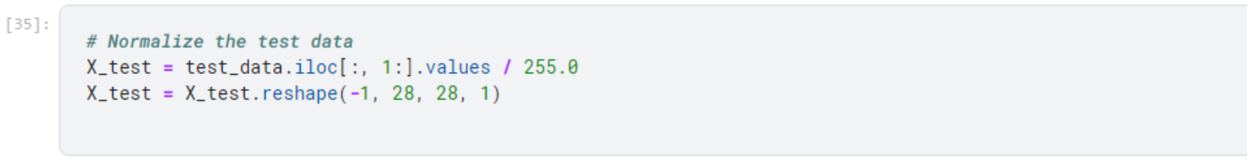
```
[34]:
# Load the test data
test_data = pd.read_csv('/kaggle/input/Kannada-MNIST/test.csv')
test_data.head()
```

[34]:

	id	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	3	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

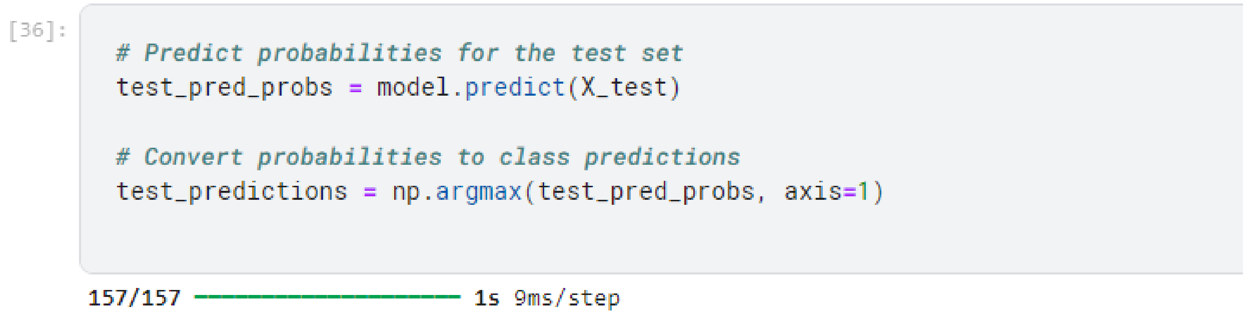
5 rows × 785 columns

Normalization: To ensure consistency between the training and test data, the same normalization technique was applied to the test images. This involved scaling the pixel values to the range [0, 1] by dividing each value by 255. Normalization is essential as it allows the model to interpret the pixel values in a similar fashion as during training, leading to more accurate predictions.



```
[35]:
# Normalize the test data
X_test = test_data.iloc[:, 1:].values / 255.0
X_test = X_test.reshape(-1, 28, 28, 1)
```

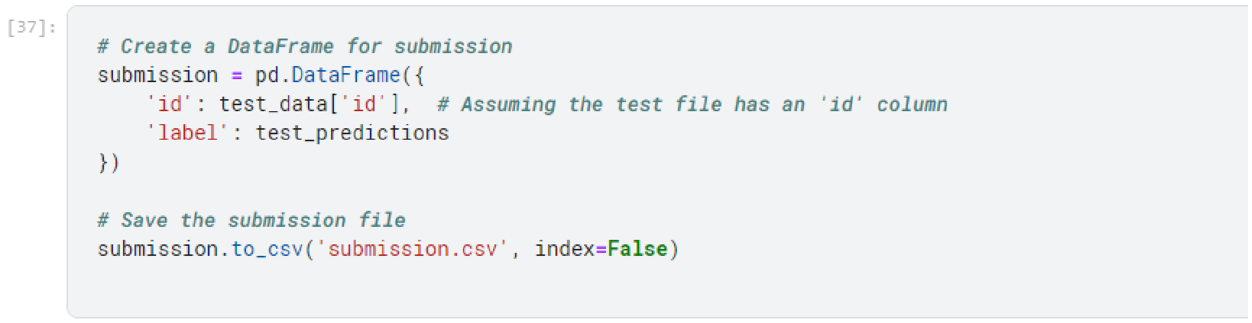
Making Predictions: Once the test data was normalized, the trained CNN model was used to predict the labels for each test image. The model outputs probabilities for each digit class (0-9), and the class with the highest probability was selected as the final prediction for each image.



```
[36]:
# Predict probabilities for the test set
test_pred_probs = model.predict(X_test)

# Convert probabilities to class predictions
test_predictions = np.argmax(test_pred_probs, axis=1)
```

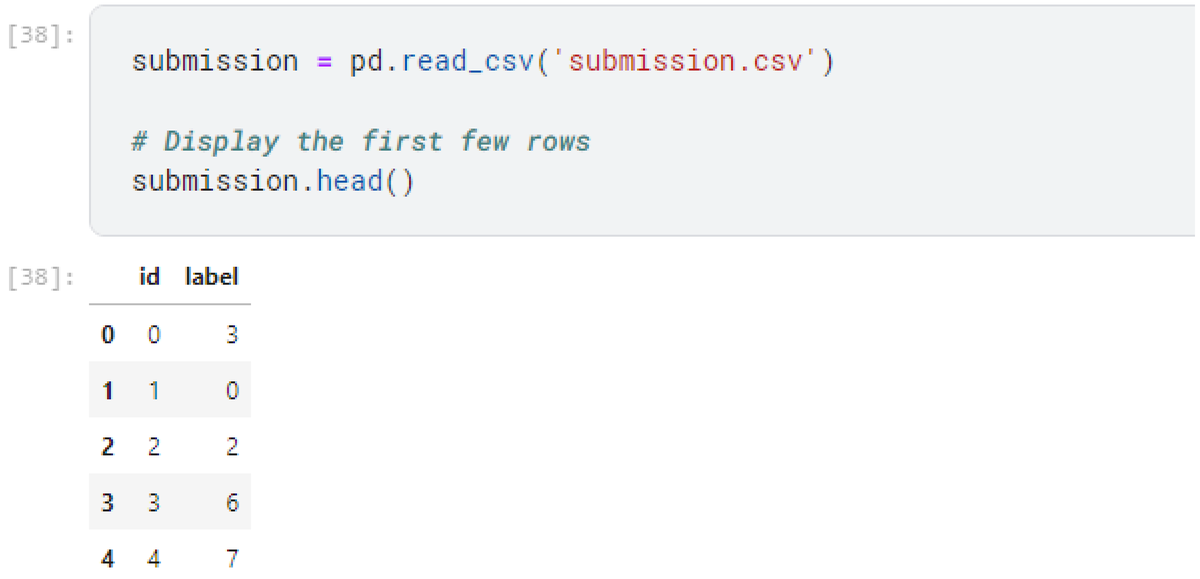
```
157/157 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step
```

Creating the Submission File: After predicting the labels, the results were compiled into a CSV file in the format required by the competition. This file included two columns: the id of each test image and the corresponding predicted label. The submission file was then generated and submitted to the competition platform.



```
[37]:
# Create a DataFrame for submission
submission = pd.DataFrame({
    'id': test_data['id'],  # Assuming the test file has an 'id' column
    'label': test_predictions
})

# Save the submission file
submission.to_csv('submission.csv', index=False)
```

Reviewing the Submission File: A final lookup on the generated file before submitting it through the Kaggle's Submit option



```
[38]:
submission = pd.read_csv('submission.csv')

# Display the first few rows
submission.head()
```

```
[38]:
      id  label
   0   0      3
   1   1      0
   2   2      2
   3   3      6
   4   4      7
```

Summary: This step is critical as it transforms the learned model into actionable predictions on new, unseen data, ultimately determining the performance in a real-world scenario or competition. The careful handling of the test data, consistent preprocessing, and accurate predictions ensure that the model's generalization capabilities are effectively evaluated.

The notebook used for this project can be found at …
https://www.kaggle.com/code/asifpeshkar/notebook5cb1e0583f

Chapter 4: Summary of Findings

In this chapter, we summarize the key findings from our detailed analysis of the Kannada MNIST classification project, elaborating on the core aspects that contributed to the model's success.

1. Data Exploration and Preprocessing:

The initial data exploration confirmed that the Kannada MNIST dataset was balanced across all ten-digit classes, ensuring that the model would not be biased towards any specific digit. The dataset consisted of 60,000 training images and 10,000 test images, each representing a 28x28 pixel grayscale image. The pixel intensity distribution revealed that most pixel values were either very low (background) or very high (digit strokes), guiding our decision to normalize the pixel values to a range between 0 and 1.

To improve the model's ability to generalize across diverse handwriting styles, data augmentation techniques were applied. These techniques included rotations, zooms, and shifts, which artificially increased the variety of images in the training set. This step was crucial in preventing overfitting and improving the model's robustness. The preprocessing phase also involved reshaping the images to fit the CNN input format, which contributed to the effective training of the model.

2. Model Development and Training:

The CNN architecture was designed with the specific challenges of Kannada digit recognition in mind. The model included multiple convolutional layers, each followed by pooling layers, which allowed the network to learn hierarchical features from the images. These features ranged from simple edges in the initial layers to more complex shapes in the deeper layers. The fully connected layers at the end of the network interpreted these features to make predictions about the digit class.

During the training phase, the model was trained over 15 epochs with a batch size of 32, using the Adam optimizer. Hyperparameter tuning played a significant role in optimizing the model's performance. Adjustments to the learning rate, batch size, and number of layers were made based on the results observed during training. The final model achieved a validation accuracy of 97.82%, indicating its effectiveness in classifying Kannada digits.

Throughout the training process, the model's performance was monitored using training and validation accuracy and loss curves. These visualizations provided insights into the model's learning process, highlighting periods of rapid learning and potential overfitting. Early in the training, the model showed signs of overfitting, which were mitigated through the use of data augmentation and slight architectural adjustments.

3. Model Evaluation and Results:

The final evaluation of the CNN model was conducted using a variety of metrics, including accuracy, precision, recall, and F1-score. The model demonstrated strong performance across all these metrics, confirming its ability to accurately classify the digits in the Kannada MNIST dataset. A confusion matrix was used to analyze the model's performance across different classes, revealing that most misclassifications occurred between digits with similar shapes, such as '4' and '9'. These findings highlighted the specific challenges posed by the Kannada script and underscored the importance of the CNN's ability to learn complex features.

Error analysis provided further insights into the model's strengths and weaknesses. By examining specific cases where the model misclassified digits, it became clear that variations in handwriting styles, low contrast, and unclear strokes were common factors leading to errors. These findings suggest that while the model performs well under typical conditions, it may struggle with more challenging inputs, pointing to areas for future improvement.

In addition to the CNN model, simpler models such as Logistic Regression, SVM, and Decision Tree were also tested for comparison. These models, while effective in simpler tasks, were unable to match the CNN's performance in this more complex classification task. The CNN's superior ability to capture and learn from the intricate patterns in the Kannada script reaffirmed its suitability for this application.

Conclusion: The findings from this project demonstrate the effectiveness of CNNs in handling complex image classification tasks, particularly for regional languages like Kannada. The thorough exploration of data, strategic model design, and comprehensive evaluation have resulted in a robust model capable of high accuracy in Kannada digit recognition. These results lay the groundwork for future work, including the potential for deploying such models in real-world applications and extending the approach to other regional scripts.

Chapter 5: Conclusions and Suggestions

1. Conclusions:

The project’s primary objective—to develop a robust and accurate model for recognizing Kannada handwritten digits—was successfully achieved. The Convolutional Neural Network (CNN) designed for this task demonstrated exceptional performance, with an accuracy of 97.82% on the validation set. This high level of accuracy is indicative of the model’s ability to effectively learn and generalize from the data.

- Strength of CNNs: The CNN model’s architecture, which includes multiple convolutional layers followed by fully connected layers, proved to be particularly effective in capturing the complex features inherent in Kannada digits. This allowed the model to distinguish between similar digits, such as '1' and '7', or '4' and '9', which are often challenging to differentiate.

- Comparison with Simpler Models: When compared with simpler models such as Logistic Regression, SVM, and Decision Tree, the CNN consistently outperformed these alternatives. The Logistic Regression model, while effective in binary classification tasks, struggled to capture the nuances of the Kannada script, resulting in an accuracy significantly lower than that of the CNN. The SVM, despite its effectiveness in various classification tasks, also fell short in handling the complexity of the handwritten digits in this context. The Decision Tree model, though useful in understanding simple decision boundaries, was less capable of generalizing from the dataset compared to the CNN.

- Error Analysis: An in-depth analysis of the model's errors provided valuable insights into its limitations. Misclassifications were primarily observed in cases where the digits were poorly written or had overlapping features. These errors highlight the challenges posed by variations in handwriting and suggest that further improvements could be made by increasing the diversity of the training data or employing more sophisticated preprocessing techniques.

2. Suggestions for Future Work:

While the project achieved its goals, there are several avenues for future work that could build upon these findings and further enhance the model's performance:

- Advanced Architectures: Future work could explore more advanced CNN architectures, such as ResNet, Inception, or DenseNet. These architectures, known for their depth and complexity, could potentially improve the model's ability to learn even more intricate patterns in the data. Implementing these architectures might also help address some of the misclassification issues identified in the current model.

- Transfer Learning: Another promising direction is the application of transfer learning. By leveraging pre-trained models on large datasets (e.g., ImageNet), the model could benefit from already learned features, which might be applicable to Kannada digit recognition. This approach could reduce training time and potentially increase accuracy, particularly when fine-tuned on the Kannada MNIST dataset.

- Data Augmentation and Synthesis: Expanding the dataset with additional handwritten samples, especially from a broader demographic, could help the model generalize better to different handwriting styles. Advanced data augmentation techniques, such as elastic distortions or synthetic data generation, could be used to create more varied training examples, further improving the model's robustness.

- Real-World Application and Deployment: The practical application of this model in real-world scenarios, such as mobile OCR tools or educational software, is a logical next step. Implementing the model in these contexts would require further optimization to ensure it operates efficiently on mobile devices or in resource-constrained environments. Additionally, real-world testing could uncover new challenges, such as dealing with noisy inputs or different lighting conditions, that would need to be addressed.

- Broader Application to Other Regional Scripts: The techniques and insights gained from this project could be applied to other regional languages and scripts beyond Kannada. Developing models for languages like Tamil, Telugu, or Bengali could contribute to the broader goal of creating robust OCR systems for Indian languages, aiding in the digitization of regional literature and administrative documents.

3. Final Thoughts:

This project not only demonstrated the effectiveness of CNNs in classifying Kannada handwritten digits but also highlighted the potential for further advancements in this field. The ability of the CNN model to outperform traditional methods underscores the importance of deep learning techniques in modern OCR applications. However, the challenges faced during the project, such as misclassifications and the need for diverse training data, indicate that there is still room for improvement.

The work done in this project lays a strong foundation for future research in the area of regional language OCR. As digitization efforts continue to grow in India, the need for accurate and efficient OCR systems for regional scripts will become increasingly critical. By building on the findings of this project, future **research** can contribute to the development of inclusive technologies that support the diverse linguistic landscape of India. The advancements made in this field could have a lasting impact on the accessibility of digital content in regional languages, bridging the gap between technology and local culture.

References

Research for academic articles on CNNs and digit classification from Kaggle, geeksforgeeks, freecodecamp and datacamp.

Kaggle dataset documentation and related resources Websites

https://www.kaggle.com/competitions/Kannada-MNIST/overview

https://www.geeksforgeeks.org/convolutional-neural-network-cnn-in-machine-learning/

https://www.freecodecamp.org/news/convolutional-neural-network-tutorial-for-beginners/

https://www.datacamp.com/tutorial/introduction-to-convolutional-neural-networks-cnns

Finally, the notebook used for this project can be found at …

https://www.kaggle.com/code/asifpeshkar/notebook5cb1e0583f