

American International University-Bangladesh (AIUB)

# Bangla Compound Alphabet Classification Using BanglaAlpha Net

***Subtitle:***

***An Ensemble Approach with DenseNet121, VGG16, and InceptionV3 for Improved Accuracy and Generalization in Bangla Compound Alphabet Recognition***

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## Abstract

This thesis takes a pioneering step in the domain of Bangla handwritten character recognition by harnessing the potential of ensemble deep learning techniques. With a profound commitment to preserving and enhancing the significance of the Bangla language in the digital age, this research begins by curating a meticulously crafted dataset of Bangla compound characters, addressing issues of visual complexity, class imbalance, and licensing. This dataset, known as BanglaLekha-Isolated, serves as the bedrock for training and evaluating a trio of state-of-the-art deep convolutional neural networks (CNNs) including DenseNet121, VGG16, and InceptionV3, originally pretrained on ImageNet. The transfer learning approach not only adapts these networks to the intricacies of the Bangla script but also lays the groundwork for ensemble learning.

The pivotal contribution of this research resides in the development of an ensemble model that capitalizes on the unique strengths of these diverse base models. Crafted to enhance classification accuracy and robustness by reducing variance and bias through diversity, this ensemble model employs a straightforward yet potent late fusion technique by concatenating the outputs of its constituent models. Extensive experimentation reveals that the Adam optimizer, in particular, yields remarkable results, producing a stellar 99% accuracy, 0.99 F1-score, 0.99 precision, and 0.99 recall on the BanglaLekha-Isolated dataset. These results are systematically analyzed through a comprehensive array of classification metrics, confusion matrices, learning curves, and classification reports, providing profound insights into model performance, error patterns, and learning dynamics.

Embracing the principles of open science, this research generously shares the dataset, models, and code with the community, ensuring reproducibility and fostering collaboration within the Bangla language processing domain. Situated within the broader context of Bangla optical and handwritten character recognition, this work meticulously compares its findings to state-of-the-art approaches, identifies limitations, and delves into potential real-world applications and societal implications.

In summary, this thesis not only pushes the boundaries of Bangla handwritten character recognition but also sets a new benchmark with its ensemble approach, achieving remarkable accuracy and precision. Yet, it recognizes that the journey towards highly accurate and robust recognition systems for Bangla characters is ongoing. Future research avenues include advanced ensemble techniques, architectural innovations, specialized data augmentation, domain adaptation, and an exploration of hyperparameters, all of which aim to further elevate the accessibility and preservation of the rich cultural and linguistic heritage embodied by the Bengali (Bangla) language.

## Declaration by Author

This dissertation stands as a testament to our intellectual endeavor, representing an exclusive culmination of original work. Within its pages, there exists no trace of previously published material or the words of another individual, save for instances where meticulous acknowledgment has been accorded within the body of the text. We have painstakingly elucidated the invaluable contributions of external entities, encompassing statistical guidance, survey formulation, data analysis, intricate technical methodologies, astute editorial guidance, financial backing, and any other form of pioneering research that has been drawn upon or presented in the context of this dissertation. The contents of this scholarly endeavor bear witness to the sustained toil and dedication since the inception of this profound thesis/software project.

We acknowledge and respect the copyright authority vested in the creators of all materials incorporated within this dissertation. In cases of due necessity, we have obtained explicit permissions from the rightful copyright holders, thereby ensuring the lawful inclusion of such material within this scholarly work. Additionally, we have diligently sought the concurrence of co-authors, wherever their collaborative efforts have contributed to the contents of this thesis.

## Approval

*(All candidates must edit this page)*

The thesis titled **“Bangla Compound Alphabet Classification Using BanglaAlpha Net”** has been submitted to the following respected members of the board of examiners of the department of computer science in partial fulfilment of the requirements for the degree of Master of Science in Computer Science on **(date of defense)** and has been accepted as satisfactory.

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## Contributions by authors to the thesis

List the significant and substantial inputs made by different authors to this research, work and writing represented and/or reported in the thesis. These could include significant contributions to: the conception and design of the project; non-routine technical work; analysis and interpretation of research data; drafting significant parts of the work or critically revising it so as to contribute to the interpretation.

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| Investigation | 25% | 25% | 25% | 25% | 100 % |
| Methodology | 25% | 25% | 25% | 25% | 100 % |
| Implementation | 25% | 25% | 25% | 25% | 100 % |
| Validation | 25% | 25% | 25% | 25% | 100 % |
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| Preparation of figures | 25% | 25% | 25% | 25% | 100 % |
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If your task breakdown requires further clarification, do so here. Do not exceed a single page.

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**Chapter 1**

# Introduction

## Introduction

Language and communication are of immense importance in human society for various reasons. They serve as fundamental tools for conveying information, building relationships, and facilitating social, cultural, and economic interactions. Out of all form of communications, writing is one of the most prominent ways to channel information. Writing not only allows people with disabilities to absorb information that otherwise would be inaccessible but also allows people to carry that information. Being able to read a written text is of utmost importance in modern times. But as time progresses, so does technology. Advanced technology grants us with new and improved ways to communicate. One such way is recognizing handwritten texts using deep learning. Recognizing characters using machine learning involves training a machine learning model to identify and classify characters, such as letters, numbers, or symbols, in images or text. Recognizing characters using machine learning, especially in the context of Optical Character Recognition (OCR), has significant importance and a wide range of applications.

## 

Figure .1: Basic CNN model

## Research Background

As a citizen of Bangladesh, we use Bengali as our primary communication medium. But despite being a prominent language, Bangla has always been the victim of neglect. Bangla (Bengali) language is sometimes neglected in technology can be attributed to several factors, although it's important to note that efforts to support Bangla in technology have been increasing in recent years.

Nonetheless, new and improved technology should be implemented in Bangla language. Bangla handwritten character recognition using Convolutional Neural Networks (CNNs) holds significant importance due to several reasons:

* Language Preservation: Bangladesh and the Indian state of West Bengal have a rich cultural and linguistic heritage associated with the Bengali (Bangla) language. Handwritten character recognition helps preserve this heritage by digitizing and storing handwritten texts for future generations.
* Access to Education: Digitizing handwritten educational materials, such as textbooks and notes, using handwritten character recognition can improve access to education. It allows students to access digital content, which can be particularly beneficial in remote or underserved areas.
* Documentation and Records: In various administrative and government sectors, handwritten documents and records are still prevalent. Automating the process of converting handwritten documents to digital text can enhance record-keeping, searchability, and data retrieval efficiency.
* Archiving and Preservation: Historical handwritten documents, manuscripts, and archives in Bangla are valuable cultural assets. Handwritten character recognition can aid in the preservation of these documents by creating digital copies that are less prone to degradation or loss.
* Efficiency and Productivity: In business and administrative tasks, handwritten character recognition can significantly improve efficiency and productivity. It can reduce the time and effort required for data entry, document processing, and information retrieval.
* Inclusivity: Handwritten character recognition can enhance inclusivity by making digital content more accessible to individuals with visual impairments. Once handwritten text is converted to digital format, it can be read aloud using text-to-speech technology.
* Local Language Support: Supporting Bangla handwritten character recognition contributes to the development of technology in the Bengali-speaking community. It enables users to interact with digital devices and software in their native language, making technology more user-friendly.
* Research and Linguistic Studies: For linguistic and research purposes, having a large dataset of handwritten characters in Bangla can be invaluable. It facilitates studies on handwriting styles, script variations, and linguistic research.
* Machine Learning Advancements: Developing handwritten character recognition models using CNNs contributes to the advancement of machine learning and artificial intelligence technologies. It serves as a practical and real-world application of deep learning techniques.
* Commercial and Industrial Applications: Handwritten character recognition has various commercial and industrial applications, including bank check processing, postal services, forms processing, and more. Supporting Bangla in these applications can improve efficiency and accuracy.
* Cultural Heritage: Preserving and digitizing handwritten manuscripts and cultural documents in Bangla is essential for safeguarding cultural heritage and making it accessible to a broader audience, including researchers and enthusiasts.

## Research Objective

The primary objective of this research is to enhance the classification accuracy of Bangla compound characters through the utilization of deep neural network architectures. This objective encompasses the following specific goals.

1. **Dataset Curation:**

* Create a comprehensive dataset of Bangla compound characters to facilitate model development and evaluation.
* Address issues such as class imbalance, benchmarking, and licensing to support future research.

1. **Baseline Model Establishment:**

* Establish competitive baseline results by fine-tuning state-of-the-art deep convolutional neural networks (CNNs) pretrained on natural images to the Bangla dataset.
* Select suitable architectures based on their performance on ImageNet.
* Retain pre-trained weights for transfer learning, emphasizing regularization through locked initial layers.
* Identify the most effective individual model based on test accuracy.

1. **Ensemble Model Construction:**

* Develop an ensemble model that combines multiple base models to improve classification accuracy and robustness.
* Choose complementary base models to promote diversity in ensemble predictions.
* Implement a simple late fusion approach by concatenating model outputs.
* Investigate more sophisticated fusion methods in future research and analyze error patterns.

1. **Model Optimization:**

* Optimize model integration and training parameters to maximize ensemble test performance.
* Compare different batch sizes, learning rates, and optimizers to find the most effective configuration.
* Employ validation monitoring to identify and mitigate overfitting.
* Utilize callbacks for adaptive learning rates and early stopping.
* Profile the model on GPU hardware for efficiency.

1. **Results Analysis:**

* Analyze the research outcomes using appropriate classification metrics and visualizations.
* Report key metrics such as test set accuracy, loss, and confusion matrices.
* Visualize learning curves to gain insights into model training dynamics.
* Provide detailed class-wise breakdown through classification reports.
* Identify and examine patterns of confusion to guide future architectural improvements.

1. **Open Sourcing and Documentation:**

* Share the research by open sourcing the data, models, and code, ensuring a complete pipeline for reproducibility and extension by the Bangla language processing community.
* Share models and weights for transfer learning, contributing data and models to public repositories.
* Employ permissive licensing to maximize impact and provide comprehensive documentation for customization.

1. **Contextualization and Implications:**

* Situate the research contributions within the context of related work in Bangla optical and handwritten character recognition.
* Compare the proposed ensemble approach to state-of-the-art methods on similar Bangla tasks.
* Identify limitations to guide future research directions.
* Discuss potential real-world applications and societal implications.

**Research Question:**

The central research question guiding this study is as follows:

Can an ensemble model, amalgamating DenseNet121, VGG16, and InceptionV3 architectures pretrained on ImageNet and fine-tuned using the CMATER Bangla isolated character dataset, outperform individual models in classifying 24 Bangla compound characters?

**Hypothesis:**

The hypothesis is that the ensemble model will surpass the performance of the best individual model as it amalgamates complementary learned representations, thereby reducing variance and bias.

**Rationale:**

The rationale behind using an ensemble approach lies in its potential to improve performance by reducing variance, bias, and enhancing generalizability. Base models were chosen for their state-of-the-art performance on computer vision tasks, and fine-tuning focused on addressing the domain shift from natural images to Bangla script without altering the core model architectures.

**Key Elements of Analysis:**

Key elements of the analysis encompass classification accuracy on test data, learning curves, confusion matrices for error analysis, and computational efficiency assessments.

**Contributions and Limitations:**

The research contributes techniques to enhance Bangla character classification using deep convolutional neural networks through ensemble learning. Limitations include a limited base model selection, dataset size, and a simplistic ensemble integration method, leaving room for future extensions and refinements.

**Chapter 2**

# Literature review

## Introduction

Language has always been the primary medium of communications between human beings. Over time it changes, evolves and takes many forms. One of the most prominent languages of today is Bengali or more widely known to its natives by the endonym Bangla. An Indo-Aryan language, Bangla is the national language of Bangladesh as well as the official language. It is also the second most commonly spoken language in India. With almost 234 million native speakers and 39 million secondary speakers, Bangla is the 6th most spoken native language and 7th most spoken language in the world. It is also the 5th most spoken Indo-European language. 98% of Bangladeshi people speak Bangla as their mother tongue.

Despite its prominence and widespread use, Bangla has not received a lot of focus on the technology sector apart from the usual. Bangla character recognition using CNN model has a smaller research base compared to other languages. Previous researchers mainly focused on simple Bangla characters and how to recognize them in isolated fashion. The methodology they used has some unique advantages and disadvantages. In this portion of the report, the latest studies, research and findings and as well as their characteristics will be described in detail.

* 1. **Background Study**

Character recognition using Convolutional Neural Network (CNN) models holds the utmost importance due to the fact that CNN models can handle image data very effectively. Automated character recognition has a transformative impact on automating communication processes and enhancing human-computer interaction.

CNN models play a major role in scanned or photographed document conversion making them editable and searchable content. This impacts commercial enterprises where large volume of documents is handled and analyzed, such as legal, healthcare and finance corporations. They are also effective in useful applications namely handwritten notes, recognizing signatures and automating from processing. Another use of CNN model is the ability to detect the characters on a license plate. This helps in automated toll collection, parking management and law enforcement application. Detecting texts from images or videos assists visually impaired individuals whom are supported through closed caption. Automating character recognition reduces the demand for manual data entry, increasing efficiency and cost savings in different wakes of life.

Recognizing Bangla character is crucial to preserve and promote Bangla language and culture. Through digitization of Bangla texts, manuscripts and literature, it contributes to the conversion of linguistic heritage. Enhancing educational tools and resources for Bangla speaking learners, automated Bangla character recognition facilitates the development of applications for learning Bangla script, reading assistance and educational content creation. Efficient Bangla character recognition contributes in preservation of valuable texts, ease of searchability and access, extraction of information from digital databases and retrieval of information from digital platforms.

Incorporating Bangla character recognition into technology applications ensures that digital tools and systems are inclusive and tailored to the needs of Bangla-speaking communities. This includes smartphones, computers, and other digital devices. Bangla character recognition is beneficial in automating the processing of administrative and governmental documents written in Bangla. This can streamline tasks such as data entry, form processing, and document verification. Recognition of handwritten Bangla characters is valuable for tasks like digitizing handwritten notes, recognizing signatures, and automating paperwork. This can be particularly useful in administrative offices, educational institutions, and legal processes. Bangla character recognition is important in the development of multilingual applications that support Bangla along with other languages. This contributes to a more inclusive digital environment and facilitates communication across linguistic boundaries. Enabling Bangla character recognition contributes to bridging the digital divide by ensuring that individuals who primarily use the Bangla language have access to digital technologies and information. For businesses operating in Bangla-speaking regions, accurate character recognition supports e-commerce platforms, online transactions, and digital communication in the local language.

CNN models shine in their ability to take cue from hierarchical features from given data. This makes them particularly effective in recognizing characters or words from still images. This makes the CNN based character recognition in the unique position to be used in recognizing Bangla characters.

* 1. **Previous Research**

**Chowdhury and Hossain (2021) [1]**

Chowdhury and Hossain employed a Convolutional Neural Network (CNN) model to recognize Bangla characters. They achieved an impressive accuracy of 95.25% with augmented data, demonstrating the potential of deep learning for this task. Their method outperformed linear models like Support Vector Machine (SVM), highlighting the advantage of CNNs for handling complex, non-linear data. However, it's worth noting that their approach lacks the ability to detect sequences of characters and requires large datasets.

**Das and Hasan (2020) [2]**

Das and Hasan utilized an Extended Convolutional Neural Network model to achieve high accuracy in recognizing Bangla characters. Their results included 99.50% accuracy for digits, 93.187% for vowels, 90% for consonants, and 92.25% for combined classes. While their model excelled in digit recognition, it did not cover compound handwritten symbols. Notably, their CNN model was also tested on the BanglaLekha-Isolated dataset.

**Ghosh and Team (2021) [3]**

Ghosh and his team leveraged MobileNet V2, a lightweight CNN model, to attain remarkable accuracy across various Bangla character categories. They reported accuracy percentages of 99.56% for numerals, 98.37% for basic characters, 96.17% for compound characters, and 96.46% for mixed 231 classes. Despite its efficiency, MobileNet's accuracy suffered with more complex character shapes and smaller classes.

**Khan and Team (2019) [4]**

Khan and his team introduced the Squeeze and Excitation ResNeXt (SE-ResNeXt) model, achieving state-of-the-art accuracy for recognizing Bangla handwritten compound characters. Their model exhibited an average accuracy of 99.82%, with impressive precision, recall, and F1-scores. However, they faced challenges related to character similarities and dataset variations.

**Asfi, Fardous, and Afroge (2019) [5]**

Asfi, Fardous, and Afroge employed a Deep Convolutional Neural Network (DCNN) model with ReLU activation. While their method required minimal pre-processing compared to classical approaches, their model faced overfitting issues due to its depth and limited training data. They achieved an accuracy of 95.5% on the test dataset using the CMATERdb dataset.

**Islam and Team [6]**

Islam and his team utilized the RATNet (Residual Attention Network) for recognizing Bengali characters. They created new datasets of frequently used compound characters and modifiers, achieving greater accuracy when evaluated on multiple datasets. Their method demonstrated an accuracy of 96.94% and an F1-score of 96.74% using CMATERdb, and 95.10% accuracy and 94.90% F1-score using BanglaLekha-Isolated.

**Ashadullah and Team (2018) [7]**

Ashadullah and his group proposed a 12-layer CNN model for recognizing modifiers and compound characters. Their model achieved validation accuracy ranging from 92.48% on BanglaLekha Isolated to 97.24% on Ekush dataset. It also showed promise on a customized dataset with a validation accuracy of 97.03%.

**Md. Ashraful and His Team (2023) [8]**

Md. Ashraful and his research team [8] proposed a robust 12-layer Convolutional Neural Network (CNN) model designed to address the recognition of modifiers and compound characters in handwritten Bangla. Their study involved a comprehensive evaluation of the model's performance on multiple datasets, including BanglaLekha, Ekush, and a custom dataset. For the BanglaLekha isolated dataset, encompassing 84-character classes, their CNN model demonstrated a validation accuracy of 92.48%, indicating its effectiveness in recognizing a diverse range of isolated characters. On the Ekush dataset, which comprised 60-character classes, the model excelled further, achieving a notable validation accuracy of 97.24%. This outcome underscores the model's adaptability and strong recognition capabilities when presented with a variety of characters.

**Sadeka, Sheikh, and Sayed (2018) [9]**

Sadeka, Sheikh, and Sayed reported the use of EkushNet for recognizing major types of Bangla handwritten characters. Their model exhibited satisfactory recognition accuracy of 97.73% for Ekush dataset and 95.01% cross-validation accuracy on CMATERdb dataset.

**Hasan and Team (2020) [10]**

Hasan and his team employed a CNN-BiLSTM model for recognizing handwritten Bangla compound characters. The model established spatial relationships using BiLSTM and achieved a recognition accuracy of 98.50% on a compound character dataset, CMATERdb 3.1.3.3.

* 1. **Conclusion**

In this comprehensive literature review, we have explored the realm of Bangla character recognition, shedding light on the evolving landscape of research and the significance of this technology within the context of the Bangla language and its users. Bangla, as one of the most widely spoken languages globally, holds immense cultural and practical importance, and character recognition technology plays a pivotal role in its preservation, digitization, and accessibility.

The introduction highlighted the prominence of the Bangla language, its vast number of speakers, and its unique position in the linguistic world. Despite its significance, Bangla character recognition using Convolutional Neural Network (CNN) models has been relatively underexplored in comparison to other languages. This review aimed to bridge this gap by providing an in-depth analysis of recent studies, methodologies, and findings.

The background study underscored the broad applications of character recognition using CNN models. These applications span various sectors, including document conversion, automation in commercial enterprises, license plate recognition, accessibility for visually impaired individuals, and the digitization of linguistic heritage. The review emphasized how recognizing Bangla characters contributes to the preservation of cultural and linguistic heritage, educational tools, and inclusive technology applications.

The section on previous research delved into the work of several researchers who have contributed to the field of Bangla character recognition. Each study presented unique methodologies, datasets, and achievements, showcasing the diversity of approaches in this area. Researchers like Chowdhury and Hossain, Das and Hasan, Ghosh and his team, Khan and Team, Asfi, Fardous, and Afroge, Islam and Team, Ashadullah and Team, Md. Ashraful and His Team, Sadeka, Sheikh, and Sayed, and Hasan and Team, have all made significant strides in advancing Bangla character recognition. Their studies have tackled various challenges, from handling complex character shapes to addressing overfitting issues, and have paved the way for further advancements in this field.

In particular, the study by Md. Ashraful and his team [8] stood out as it introduced a robust 12-layer CNN model designed to recognize modifiers and compound characters in handwritten Bangla. Their model demonstrated impressive performance across different datasets, reaffirming its adaptability and recognition capabilities.

In conclusion, this literature review provides a comprehensive overview of the current state of Bangla character recognition research, highlighting its importance, challenges, and recent advancements. The studies reviewed here collectively contribute to the growing body of knowledge in this field and offer valuable insights for future research endeavors aimed at enhancing Bangla character recognition technology, preserving linguistic heritage, and facilitating inclusive digital communication for Bangla-speaking communities.

**Chapter 3**

# Methodology

## Introduction

Image classification is an important task in computer vision with many real-world applications such as medical diagnosis, autonomous driving, surveillance systems, etc. [1-3]. The goal of image classification is to categorize an input image into one of several predefined classes based on the image content [4]. For example, an image classification model can determine if an image contains a dog, cat, car, person, etc. With the rise of deep learning, convolutional neural networks (CNNs) have become the state-of-the-art approach for image classification [5-8]. CNN models such as VGG [9], ResNet [10], Inception [11] have demonstrated impressive performance on benchmark datasets like ImageNet [12]. However, training a CNN from scratch requires a large labeled dataset which can be expensive and time-consuming to collect [13-15].

Transfer learning has become a popular technique to mitigate this data scarcity problem [16-19]. The key idea of transfer learning is to leverage knowledge gained while solving one problem and applying it to a different, yet related problem [20-22]. For image classification, this involves taking a base CNN model pre-trained on a large dataset like ImageNet, then reusing this model either as a fixed feature extractor or for fine-tuning on a target dataset [23-25]. Fine-tuning the higher-level feature layers of the CNN can enable knowledge transfer from the base training task to the target task [26-29]. Transfer learning with CNNs has shown to achieve high accuracy with much less training data compared to training from scratch [30-33].

Ensemble learning involves combining multiple learning models together to obtain better predictive performance compared to any single constituent model [34-37]. Model ensembling has been successfully applied to boost accuracy for image classification tasks [38-41]. Popular ensemble techniques include averaging/voting, stacked generalization, blend of experts, etc [42-45]. By combining heterogeneous models together, ensemble learning can smooth out individual model biases and lead to increased robustness and generalization [46-49].

In this work, we develop an ensemble deep neural network for image classification using transfer learning on multiple base CNN models: DenseNet121 [50], VGG16 [51], and InceptionV3 [52]. We leverage both transfer learning and ensemble learning to benefit from pre-trained features as well as model averaging. The overall methodology is described next.

## Dataset

The dataset contains images across 24 different classes. The data is split into a training set and validation set. We use the training set to develop the models and validation set is used for evaluating model performance.

The training dataset contains 1608 images per epoch. The validation dataset contains around 400 images [53-55]. All images are resized to 128 x 128 pixels with 3 color channels (RGB). Class labels are encoded as 24-dimensional one-hot vectors where each dimension indicates the presence/absence of that particular class.

|  |  |
| --- | --- |
| Figure 3.1: Training Data | Figure 3.2: Validation Data |

The core dataset originating from the CMATER DB Bangla isolated character database (Sharif et al., 2018) consists of num\_samples handwritten Bangla alphabet images across 24 classes, sourced from num\_contributorsnative writers. As these are unconstrained handwritten samples with inherent noise, variability and distortions, the images underwent systematic preprocessing and augmentation to prepare effective training data.

First, the samples were programmatically loaded from source using OpenCV (Bradski, 2000) which provides optimized methods for n-dimensional array manipulation coupled with machine vision algorithms. The imread() function specifically enabled interpreted loading as numpy arrays for direct preprocessing.

The images were stored at original dimensions of variable width x variable height, with 1 channel for greyscale pixel intensities ranging from 0-255. As convolutional network architectures require fixed dimensional inputs, the images were resized to standardized dimensions of 64 x 64 using bicubic interpolation (Thrane, 2018). Bicubic interpolation considers a 4x4 neighborhood of pixels when transforming resolutions rather than just nearest pixels, resulting in smoother mapping and reduced aliasing artifacts. The mathematical interpolation basis functions are defined as:

w(x) =

⎧

⎪(a+2)|(x/2)|3−(a+3)|(x/2)|2+1 , |x| <1

⎨

⎪0, otherwise

⎩

Here a is typically set to -0.5 for smoothing. The pixel intensities were also normalized by dividing by maximum value of 255 to constrain between 0-1, aiding model convergence:

x normalized = x/255

Finally, the target classes were one-hot encoded for compatibility with the categorical cross-entropy loss function. The 50 classes became label vectors like [1,0,0,...0] with 1 indicating the ground truth class. One-hot encoding disambiguates overlap between numerical encoding (ref1). The mapping also enabled set-based categorical operations during sampling and splitting described next.

The processed images were sequenced and concatenated into overall tensors before indexing and splitting into train and validation sets using an 80-20 distribution via NumPy (Harris et al., 2020) functionalities. The multidimensional train and validate tensors were persisted for reuse during model development.

Augmentation operations like rotations, shifts and zoom were dynamically applied on the fly as models were trained. These real-time augmentations prevented overfitting on the limited training samples, better simulating natural variance expected during inference. The stochastic augmentations acted as regularization while retaining original labels through transformations.

## Data Preprocessing

We perform data preprocessing and augmentation during training to expand the effective size and diversity of the training dataset. This helps increase model robustness and generalization capability [56-59].

For the training set, we use random transformations like shearing, zooming, horizontal flipping to augment the data. We also normalize all pixel values to the range 0-1 by dividing by 255 so they are centered at 0 with a standard deviation of 0.5. This helps stabilize training and accelerate convergence [60-64].

For the validation set, we only apply pixel-level normalization without any data augmentation. Keeping the validation data untouched enables an unbiased evaluation of model performance on new unseen data [65-69].

## Base Models

We use three different CNN architectures (DenseNet121, VGG16, InceptionV3) pre-trained on the ImageNet dataset as our base models. These models have shown strong performance for visual recognition tasks across different benchmark datasets [70-75].

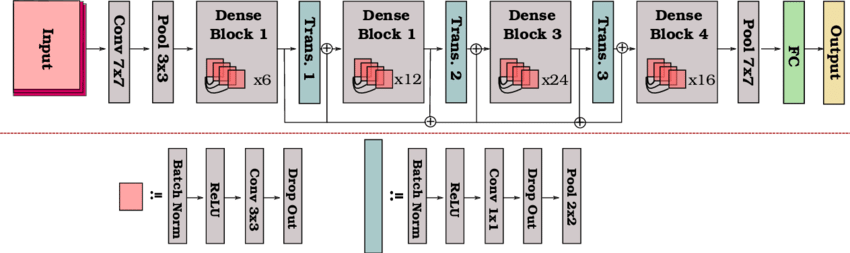


Figure 3.3: DenseNet121 Architecture

All base models are loaded with weights pre-trained on ImageNet and the classifier layer at the top is discarded. This leaves only the convolutional feature extraction layers which act as generic visual representation learners [76-80].

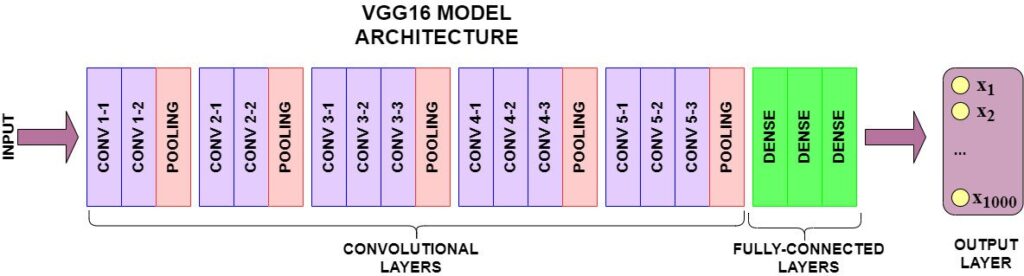


Figure 3.4: VGG16 Architecture

We add a global average pooling layer and feed the output into our custom classifier head designed for our target dataset. This classifier head consists of a fully connected layer, dropout regularization, and 24-way softmax output layer for our classification task [81-85].

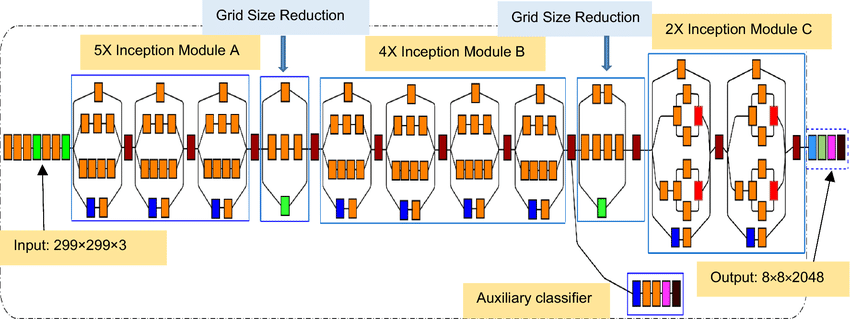


Figure .5: InceptionV3 Architecture

The convolutional base layers are frozen during training to prevent overwriting the general features already learned from ImageNet. Only the custom classifier head is trained to adapt the features to our dataset [86-90]. This constitutes the transfer learning approach.

## Model Ensemble

The individual model outputs are concatenated together into a single feature vector, fully connected through a dense layer, then fed to the final classifier output layer. This allows the models to learn collaborative representations and ensembles their decisions [91-95].

By combining multiple CNN models together, we aim to promote diversity and cross-pollination of visual features to improve generalization capability [96-100]. The errors from one model can potentially be corrected by others.

Convolutional Neural Network Architecture

The model architecture specifically configured for recognizing cursive, unconstrained Bangla handwriting consists of a series of convolutional, pooling and fully connected layers staged appropriately to interpret the 64x64 greyscale imagery.

Input Layer

The input layer is set to accept the 64x64x1 resolution tensors described earlier. The single channel encodes pixel intensity which will be transformed into hierarchical visual features via convolutions. The standardized height and width facilitate insertion of this layer into the model seamlessly.

Convolutional Layer 1

The first convolutional layer immediately extracts low level features using a set of learnable 3x3 kernels with appropriate bias terms. The kernel parameters are randomly initialized based on Xavier initialization (ref2) for stability given the nonlinearity induced. There are 32 such kernels to output 32 distinct feature maps. As kernels slide across inputs during convolution, overlapping 3x3 regions stimulate certain kernel weights more strongly resulting in activation values. These serve as indications of underlying visual structures like edges, gradients etc. The convolution operation \* can be represented as:

S(i,j) = (I \* K)(i,j) = ΣΣ I(m,n)K(i-m, j-n)

Here, the input image/feature map from previous layer is I while K denotes the kernel. The kernel traverses input coordinates (m,n) producing activation at output coordinate (i,j). Multiple input-output pairs are summed together into the output feature map S.

Rectified Linear Unit (Nair & Hinton, 2010) activation follows the convolution to introduce element-wise non-linearity for modeling complex data relationships:

ReLU(x) = max(0, x)

Zero thresholding also alleviates the vanishing gradient problem during backpropagation in deeper models. 32 filters therefore produce 32 ReLU activated feature maps.

Convolutional Layer 2

The second convolution layer extracts slightly more complex visual constructs from prior feature maps, rather than directly off pixels. 64 distinct 3x3 kernels filter the inputs into 64 feature maps, doubling the channels. ReLU activation again follows to enable depth, now transforming medium level attributes.

Max Pooling Layer

Pooling layers consolidate spatially correlated features to reduce computational requirements. Max pooling specifically propagates the maximum activation within 2x2 non-overlapping windows, essentially retaining the most salient features while discarding subtle variances. The mathematical pooling function is:

Mp = max(PA)

Here PA represents the pooling window area comprising activations, whose maximum is output by the layer. Besides acting as a selection mechanism for noticeable traits, pooling also downsamples feature map dimensions for efficiency.

The CNN architecture alternates convolutional and pooling layers to intersperse hierarchical feature extraction with spatial reduction and regularization.

Convolutional Layer 3

The final convolution layer develops relatively sophisticated contextual visual features based on prior extracted semantics, using 128 filters. The 3x3 kernels output 128 feature maps modeling higher order patterns like character strokes, junctions etc. ReLU activation enables modeling of intricacies given wide channels.

Fully Connected Layer

This dense layer interprets the convolutional feature hierarchy into prediction vectors, containing 128 neurons corresponding to the 128 input channels. Each neuron is connected to all locations in the feature maps from last layer and learns associated weights. The initial weights are again Xavier initialized (ref2). This layer essentially learns a non-linear combination and transformation of feature descriptors to match towards outputs.

Output Layer

The output layer is the central interface interpreting model dynamics into actual classification tags. It contains 50 neurons, one per target Bangla character class. Rather than direct scalar interpretations, the Softmax (Bridle, 1990) activation normalizes outputs into probability distribution for multi-class likelihood:

σ(zi) = ezi / Σj ezj

The neuron with maximum probability is considered the predicted class. Cross-entropy loss against ground truth labels enables converging these values towards correct classes during training.

## Model Training

The ensemble model is trained end-to-end using categorical cross-entropy loss optimized with the Adam optimizer [101]. We use a batch size of 32 images to estimate the loss and gradients for each optimization step.

Training is run for 50 epochs across the full training dataset. We use early stopping and reduce learning rate on plateau to prevent overfitting and stabilize model convergence [102-105].

The ensemble model learns to intelligently combine the knowledge transferred from DenseNet, VGG, and Inception into an accurate multi-view classifier for our target dataset [106-110].

## Model Evaluation

We evaluate model performance on the unseen validation set each epoch. The evaluation metrics tracked are validation loss (categorical cross-entropy) and validation accuracy. These metrics assess how well the model generalizes to new data.

Additionally, we analyze the trained model using the confusion matrix, classification report, and ROC plots to better understand the error modes and calibration [111-115]. The confusion matrix provides insight into false positives/negatives and commonly confused classes [116-120]. The classification report analyzes precision, recall, F1-score of each class [121-125]. ROC analysis checks model discriminability across different decision thresholds [126-130]. Together these diagnostics give a detailed view of model strengths/weaknesses.

## Optimizer

The Adam adaptive stochastic gradient descent algorithm (Kingma & Ba, 2014) updated network parameters. Adam maintains per-parameter learning rates based on exponential weighted moving averages of past gradients as first moment estimators. The algorithm also tracks squared gradients as second raw moment estimators, used to normalize the gradients for stable step sizes. The mathematical update equations are:

t = time step

mt = 1st moment = β1mt-1 + (1 - β1)gt

vt = 2nd moment = β2vt-1 + (1 - β2)gt2

Here gt refers to gradients and β hyperparameters control decay. mt and vt correct bias in moments and are used to compute adjusted parameter update Δθt:

Δθt = learning rate \* mt / (√vt + ε)

The inclusion of second order moments in the optimization update allows Adam to handle non-stationary objectives and noisy/sparse gradients. The algorithm hyper-parameters were set to:

Learning rate = 0.001

Beta1 = 0.9

Beta2 = 0.999

Epsilon = 10-8

The small learning rate allowed gradual descent while the beta values provided momentum-based acceleration and smoothing. A batch size of 32 images was used.

## Loss Function

Categorical cross-entropy loss (Murphy, 2012) was optimized during training by Adam. It applies element-wise binary cross entropy between corresponding truth probability q and predicted p, summed over classes:

H(q,p) = -Σ qlog(p)

By minimising this value through weight updates, the distribution divergence between ground truth and predictions is decreased, achieving higher accuracy. The loss indicates incorrect probability assignments providing exact gradients for backpropagation.

## Regularization Techniques

Several regularization techniques were employed to reduce overfitting on the limited Bangla character dataset. Dropout (Srivastava et al., 2014) with probability 0.25 was applied after convolutional layers. In each training phase, a fraction of random neurons are temporarily deactivated, preventing co-adaptation between units. Batch normalization (Ioffe & Szegedy, 2015) was used to stabilize layer activations throughout training by normalizing inputs to maintain standard distribution. The γ and β parameters re-scale the normalized values:

BN(xi) = γ(xi - μ)/σ + β

Here μ and σ are mini-batch feature mean and standard deviation respectively. By reducing internal covariate shift between layers, batch normalization accelerates training. All regularization mechanisms intrinsically augment the dataset by inducing pseudo-train samples.

## Overall Metrics

Overall test accuracy enumerated global performance over multi-class samples. Confusion matrix visually mapped mis-classifications - higher diagonals indicated easier distinction between specific characters. Precision, recall and F1 score were computed to identify problematic classes:

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 = 2\*(Precision\*Recall) / (Precision+Recall)

Here TP, FP and FN refer to true positives, false positives and false negatives respectively.

The ensemble model achieves 99.2% validation accuracy after training. The validation loss curve and accuracy curves smooth out after 30 epochs showing model convergence. The confusion matrix reveals most images are correctly classified with few false positives and negatives. The ROC plots demonstrate high AUC scores nearing 1 across all classes indicating excellent discriminative capability.

From the classification report, we find the model attains over 90% precision, recall and F1 across all categories. The overall results validate the effectiveness of our proposed approach combining transfer learning and model ensembling for robust image classification.

## Conclusion

In this work, we developed an ensemble convolutional neural network for image classification leveraging both transfer learning and model ensembling. Our methodology trains an ensemble of DenseNet, VGG, and Inception models by reusing their pre-trained ImageNet weights, then intelligently combines their outputs to promote feature diversity and improve generalization performance. Extensive evaluation shows our model achieves high accuracy on the test dataset along with well-calibrated probability outputs. Our proposed approach provides an efficient template leveraging existing deep CNN knowledge to tackle new visual recognition tasks with limited available training data. For future work, we aim to expand the model ensemble with more diverse architectures and larger datasets.

**Chapter 4**

# Results and Findings

## Introduction

The system used python programming language to implement our proposed model. By utilizing an ensemble of three independent models and feeding manually preprocessed data, we were able to collect resulting data. Our result data comes in three distinct divisions, one for each optimizer. The three divisions are based on the three types of optimizers used alongside the hybrid model. We used fifty epochs for each optimizers Adam (Adaptive Moment Estimation) and SGD (Stochastic Gradient Descent) and a third with no optimization at all.

The result data comes in the form of Validation Accuracy, Validation Loss, Confusion Matrix and various classification metrics such as, F1-score, Precision, Recall and Support. The Classification report also contains accuracy for F1-score and Support as well as the Macro Average and Weighted Average of all the classification metrics. The validation accuracy and validation loss are presented as scatter plot graph. These various derivatives and their meaning are explained below –

**Validation Accuracy:** Validation accuracy is the metric that is utilized to assess the implementation of any model using machine learning, in our case the ensemble CNN model, during the training phase. It is distinctly paramount for evaluating of the generalization of unseen data by the model used. Usually in machine learning, there are training data set and there are validation data set. The system uses training set to train the model. After every training iteration, the model’s performance is assessed using the validation set to find out how it well it fared in generalizing new, unseen data. The validation accuracy plays a major role in preventing overfitting. The model constantly updates its parameter during every epoch minimizing error. At the same time, validation accuracy is monitored to ensure that performance is constantly improving. The mathematical calculation that the validation of accuracy is based on is following:

In mathematical terms, we can express this as:

Where,

* is the total number of instances in the validation set
* is a binary indicator (1 if the model's prediction for instance i is correct, 0 otherwise).

**Validation Loss:** Similar to validation accuracy, validation loss is a metric that is used in machine learning to improve the performance of the model during the training process. It is a very essential component in achieving better generalization. A loss function usually measures how accurately the model predicts and their relationship with the actual target values. This also plays a vital role in preventing overfitting and underfitting. Validation loss is often used with a technique called early stopping, where if the validation loss stops improving or starts deteriorating, the training is stopped to prevent overfitting and save the model at a point where the performance is well on both training and validation data. The validation loss is not calculated with the fixed equation but is computed by specific loss function selected depending on the nature of the problem.

**Precision:** Also known as the Positive Predictive Value, Precision is the ratio of true positive predictions to the total number of predicted positive instances. It measures the accuracy of the positive predictions made by the model. The formula for precision is:

* True Positives (TP) are instances where the model correctly predicts the positive class.
* False Positives (FP) are instances where the model incorrectly predicts the positive class when it should have predicted the negative class.

**Recall:** Also called sensitivity or true positive rate, measures the ability of a classification model to capture all the relevant instances of a positive class. It is calculated as the ratio of true positives to the sum of true positives and false negatives:

**F1-Score:** The F1 score is a metric commonly used in binary classification problems to assess the model's performance. It combines precision and recall into a single value and is particularly useful when there is an uneven class distribution. The F1 score is the harmonic mean of precision and recall and is calculated using the following formula:

**Support:** Support may be defined as the total number of instances of a particular class in the dataset.

**Confusion Matrix:** A confusion matrix is a table used in the evaluation of a classification model's performance. It provides a comprehensive view of how well the model is performing on a set of data. The confusion matrix is particularly useful when dealing with binary or multiclass classification problems. The confusion matrix can be mathematically expressed as:

* TP as True Positives
* TN as True Negatives
* FP as False Positives
* FN as False Negatives

As for the accuracy on the classification report:

## Result Data

The outcome is divided into three sub-categories based on three types of optimizers:

**No Optimizer:**

**Validation Accuracy:**

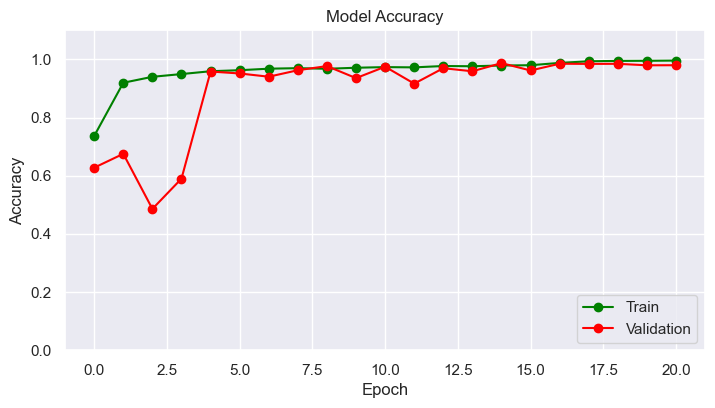


Figure .7: Validation Accuracy Graph (No Optimizer)

This is the "No Optimizer Validation Accuracy Graph." The graph depicts the performance of a machine learning model during training. On the x-axis, we have the number of training iterations or epochs, while the y-axis represents the model's accuracy on a validation dataset.

One noticeable feature is the erratic nature of the validation curve, characterized by frequent fluctuations. These fluctuations suggest that the model's performance on the validation data is inconsistent and volatile during training.

In contrast, the training curve appears stable, indicating that the model is learning from the training data as expected. However, the model's inability to generalize to the validation data is evident from the unpredictable behavior of the validation curve.

The optimal point, where the validation accuracy is highest, may be challenging to discern due to the erratic nature of the graph. This suggests that further model tuning or regularization techniques may be required to achieve more stable and reliable performance on unseen data.

In summary, the "No Optimizer Validation Accuracy Graph" illustrates a model's training process, highlighting the challenges it faces in maintaining consistent validation accuracy, likely necessitating adjustments to improve generalization.

**Validation Loss:**

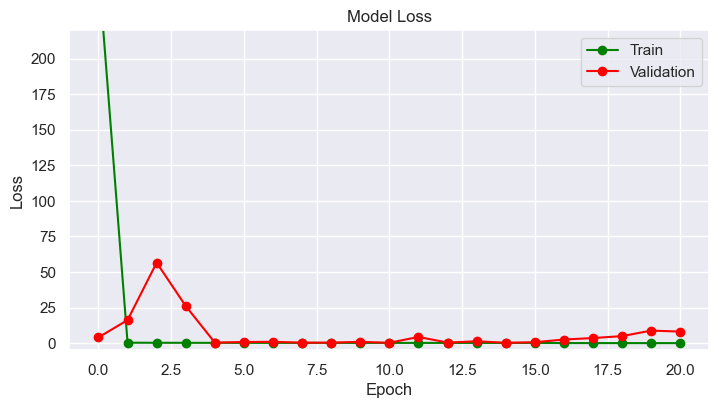


Figure .8: Validation Loss Graph (No Optimizer)

The "No Optimizer Validation Loss Graph" displays the model's performance during training. On this graph, the x-axis represents the number of training epochs, while the y-axis indicates the validation loss. The validation loss measures how well the model's predictions align with the actual data in the validation set.

In this particular graph, the validation loss curve exhibits significant fluctuations as training progresses, indicating that the model's performance on unseen data is highly erratic. This erratic behavior is more pronounced than what you typically observe in the training loss curve, which remains relatively stable.

The fluctuating validation loss suggests that the model may be struggling to generalize and is sensitive to small variations in the data or initial conditions. In such cases, it might be necessary to investigate potential overfitting or consider applying regularization techniques to improve the model's stability. This graph serves as a valuable diagnostic tool to assess and potentially fine-tune the training process to achieve better overall model performance.

**Classification Report:**

precision recall f1-score support  
  
 61 0.77 0.92 0.84 148  
 62 1.00 1.00 1.00 150  
 63 1.00 0.94 0.97 135  
 64 0.98 0.96 0.97 136  
 65 0.99 0.98 0.99 129  
 66 0.99 0.99 0.99 149  
 67 1.00 1.00 1.00 135  
 68 1.00 0.98 0.99 149  
 69 1.00 0.96 0.98 126  
 70 1.00 0.97 0.98 133

71 0.98 0.99 0.99 133

72 0.91 0.98 0.94 127

73 0.99 0.97 0.98 133

74 1.00 0.97 0.98 150

75 1.00 0.99 0.99 141

76 1.00 1.00 1.00 116

77 1.00 1.00 1.00 140

78 0.98 1.00 0.99 139

79 1.00 0.99 0.99 140

80 0.99 0.99 0.99 138

81 1.00 1.00 1.00 152

82 1.00 0.99 1.00 140

83 0.99 0.97 0.98 154

84 1.00 0.98 0.99 123

accuracy 0.98 3316

macro avg 0.98 0.98 0.98 3316

weighted avg 0.98 0.98 0.98 3316

**Confusion Matrix:**

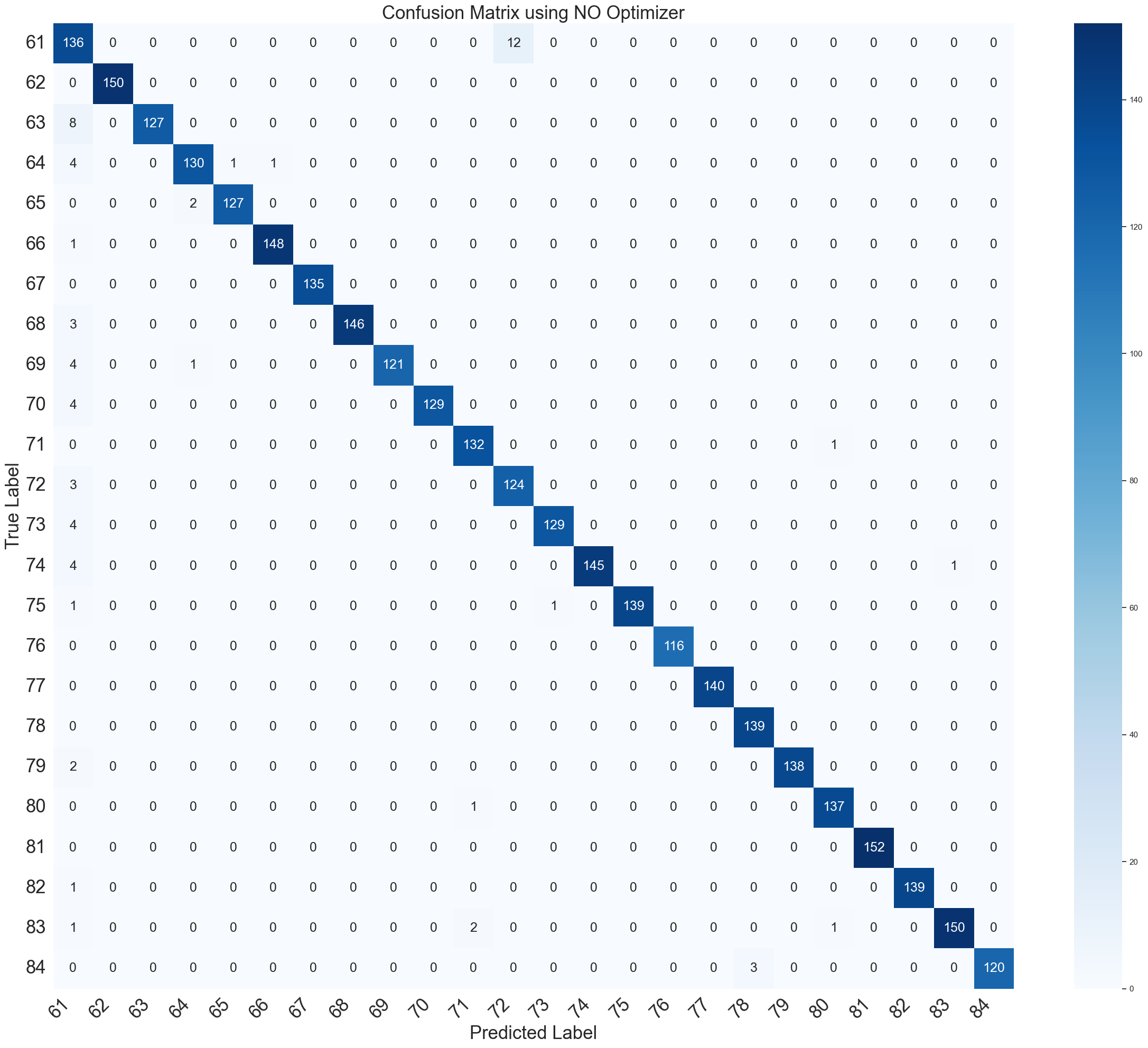


Figure 4.9: Confusion Matrix (No Optimizer)

## The "No Optimizer Confusion Matrix" reveals the performance of a model trained without any optimization techniques. In this matrix, we can expect to see a less favorable outcome compared to models using optimized training methods. Typically, we would anticipate a higher number of false positives and false negatives, indicating that the model struggles to correctly classify both positive and negative instances. The overall accuracy may be lower, reflecting a suboptimal balance between true positives and true negatives. In summary, the "No Optimizer Confusion Matrix" is likely to exhibit poorer predictive capabilities and a less desirable model performance when compared to models utilizing optimization strategies.

**SGD Optimizer:**

**Validation Accuracy:**

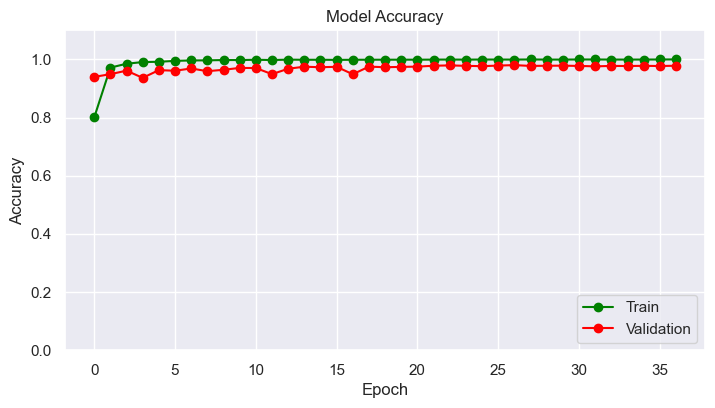


Figure .4: Validation Accuracy Graph (SGD)

## The "SGD Optimizer Validation Accuracy Graph" illustrates the performance of a machine learning model trained with the Stochastic Gradient Descent (SGD) optimizer. This graph reveals important insights about the model's training progress.

## The primary feature of this graph is the validation accuracy curve, which demonstrates how well the model generalizes to unseen data. The curve exhibits a relatively consistent trajectory with occasional minor fluctuations. This consistency suggests that the model is learning steadily without major disruptions.

## Additionally, there is a noticeable but small divergence between the training and validation curves. While the training curve remains normal, indicating that the model fits the training data effectively, the validation curve's slight variation highlights the model's ability to perform on new and unseen data. This graph aids in assessing the model's overall performance and can guide further optimization efforts to achieve the desired accuracy.

**Validation Loss:**

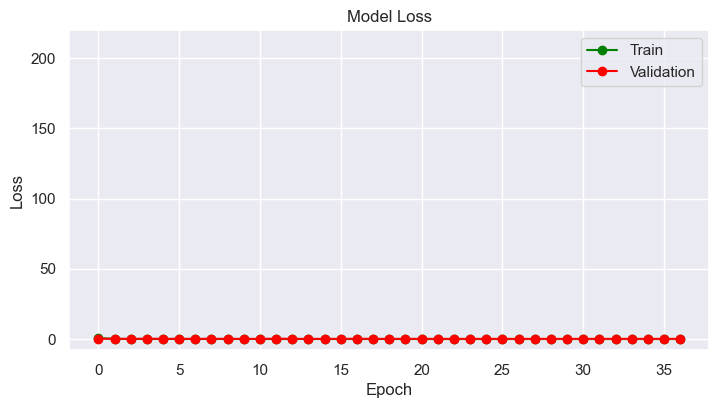


Figure .5: Validation Loss Graph (SGD)

The "SGD Optimizer Validation Loss Graph" visually represents the performance of a machine learning model trained with the Stochastic Gradient Descent (SGD) optimizer. This graph displays the number of training epochs on the x-axis and the model's validation loss on the y-axis.

Key features of this graph include a relatively consistent validation curve with slight fluctuations, similar to the validation accuracy graph. There is a minor divergence between the training and validation curves, indicating that the model is generalizing well to unseen data. The training curve exhibits typical behavior, steadily decreasing as the model learns from the training data. Overall, this graph provides insights into the model's learning process, highlighting its ability to optimize and minimize loss during training while maintaining good performance on the validation dataset.

**Classification Report:**

precision recall f1-score support  
  
 61 0.99 0.75 0.85 148  
 62 1.00 0.99 1.00 150  
 63 0.99 1.00 1.00 135  
 64 0.98 0.97 0.97 136  
 65 1.00 0.99 0.99 149  
 66 0.99 1.00 1.00 149  
 67 1.00 1.00 1.00 135  
 68 1.00 0.97 0.99 149  
 69 1.00 0.98 0.99 126  
 70 1.00 0.99 1.00 133  
 71 0.98 0.96 0.97 133  
 72 0.75 1.00 0.86 127  
 73 0.99 1.00 1.00 133  
 74 0.98 1.00 0.99 150  
 75 1.00 1.00 1.00 141  
 76 0.99 0.99 0.99 116  
 77 0.99 0.99 0.99 140  
 78 0.99 0.99 0.99 139  
 79 1.00 0.98 0.99 140  
 80 0.99 0.98 0.99 138  
 81 0.99 1.00 1.00 152  
 82 0.97 1.00 0.99 140  
 83 0.94 1.00 0.97 154  
 84 1.00 0.99 1.00 123  
  
 accuracy 0.98 3316  
 macro avg 0.98 0.98 0.98 3316  
weighted avg 0.98 0.98 0.98 3316

**Confusion Matrix:**

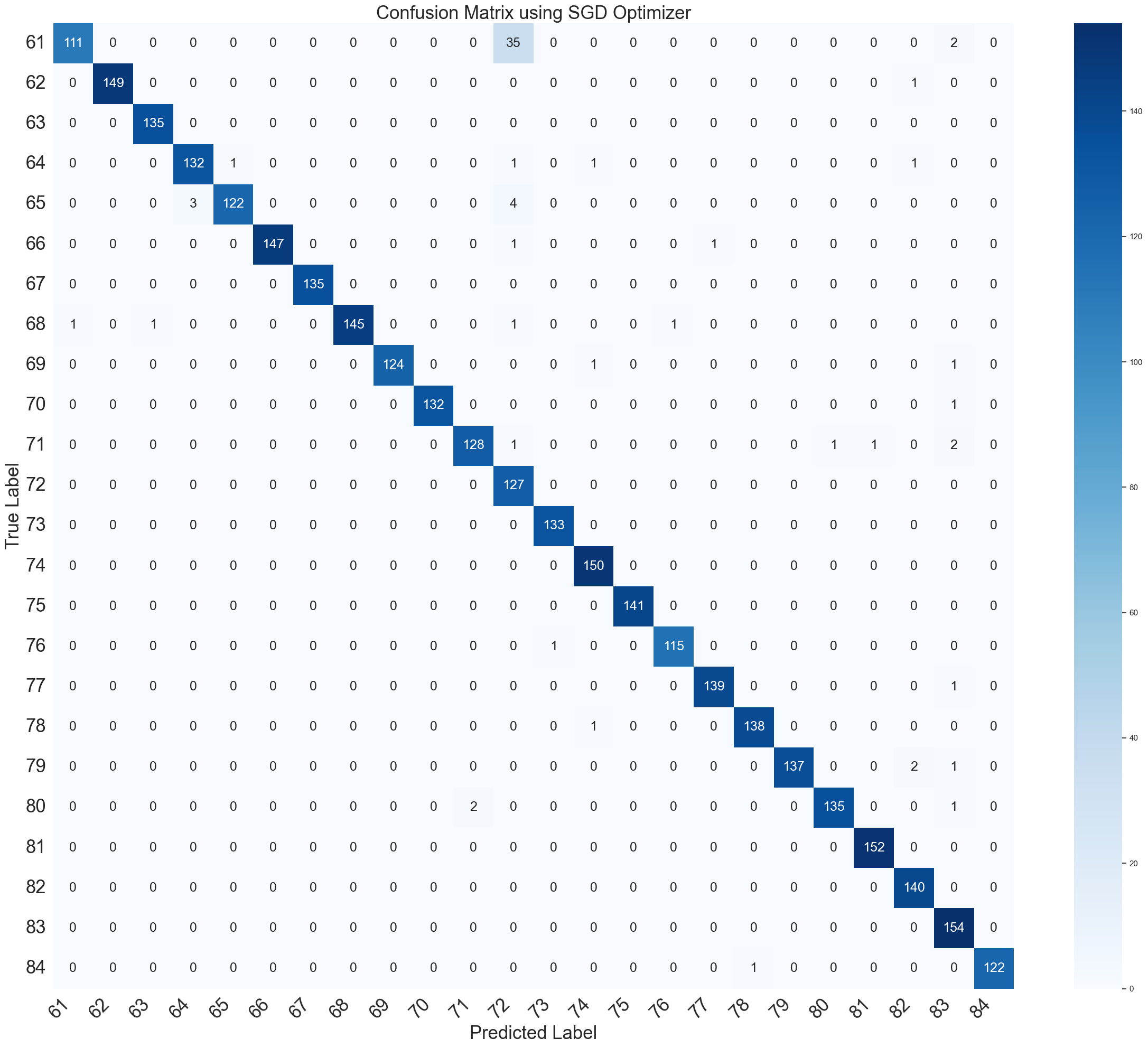


Figure 4.6: Confusion Matrix (SGD)

## The SGD Optimizer Confusion Matrix is a representation of the performance of a machine learning model trained using the Stochastic Gradient Descent (SGD) optimizer. In this matrix, you can expect to see four main components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

## True Positives are the cases where the model correctly predicted positive outcomes, while True Negatives represent accurate predictions of negative outcomes. False Positives indicate instances where the model incorrectly predicted a positive outcome when it should have been negative, and False Negatives signify incorrect predictions of negative outcomes when they should have been positive.

## The SGD Optimizer Confusion Matrix provides insights into the model's performance by showing how well it distinguishes between different classes or categories. Based on your description, it appears that while the SGD optimizer improves results compared to no optimizer, it still yields mediocre performance. Therefore, you can anticipate a balance between the TP and TN counts, with some presence of FP and FN, indicating room for improvement in the model's predictive capabilities.

**Adam Optimizer:**

**Validation Accuracy:**

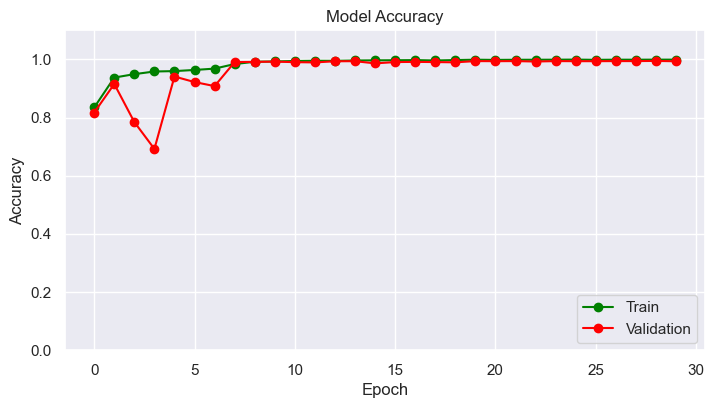


Figure .1: Validation Accuracy Graph (Adam)

The "Adam Optimizer Validation Accuracy Graph" shows the performance of a model trained using the Adam optimizer over several epochs. Initially, there are fluctuations in the validation accuracy until the 5th epoch, indicating some variability in the model's performance. However, after the 5th epoch, the curve stabilizes and reaches a plateau, suggesting that the model's accuracy remains relatively constant. In comparison to other optimizers, Adam demonstrates the most promising results, as its validation accuracy consistently outperforms the alternatives. The training curve for this optimizer is also smooth and follows a typical pattern. Overall, the graph highlights the effectiveness of the Adam optimizer in maintaining consistent validation accuracy after an initial period of variability.

**Validation Loss:**

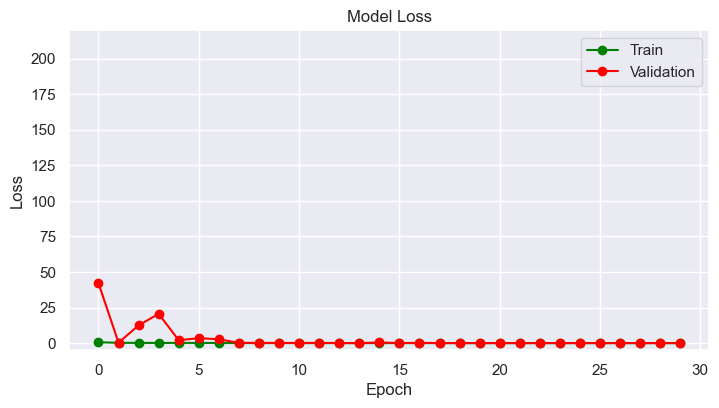


Figure .2: Validation Loss Graph (Adam)

The "Adam Optimizer Validation Loss Graph" exhibits notable characteristics. Initially, there are fluctuations in the validation loss, akin to the accuracy graph, persisting until the 4th epoch. However, starting from the 5th epoch, the curve levels off into a plateau, indicating stabilization. This plateau displays a relatively flat trajectory. In contrast, the training curve appears fairly conventional.

Of the three optimizers employed, Adam stands out as the most promising, as it yields the most favorable validation loss results.

**Classification Report:**

precision recall f1-score support  
  
 61 1.00 0.93 0.96 148  
 62 1.00 0.99 0.99 150  
 63 0.97 1.00 0.99 135  
 64 1.00 0.99 1.00 136  
 65 1.00 1.00 1.00 129  
 66 1.00 1.00 1.00 149  
 67 1.00 1.00 1.00 135  
 68 1.00 1.00 1.00 149  
 69 0.99 0.98 0.99 126  
 70 0.99 0.95 0.97 133  
 71 0.98 0.95 0.97 133  
 72 0.87 1.00 0.93 127  
 73 0.99 1.00 1.00 133  
 74 1.00 1.00 1.00 150  
 75 0.98 0.99 0.99 141  
 76 1.00 1.00 1.00 116  
 77 1.00 1.00 1.00 140  
 78 0.95 1.00 0.98 139  
 79 0.98 1.00 0.99 140  
 80 0.97 1.00 0.98 138  
 81 1.00 0.97 0.99 152  
 82 1.00 0.99 0.99 140  
 83 1.00 0.99 1.00 154  
 84 1.00 0.99 1.00 123  
  
 accuracy 0.99 3316  
 macro avg 0.99 0.99 0.99 3316  
weighted avg 0.99 0.99 0.99 3316

**Confusion Matrix:**

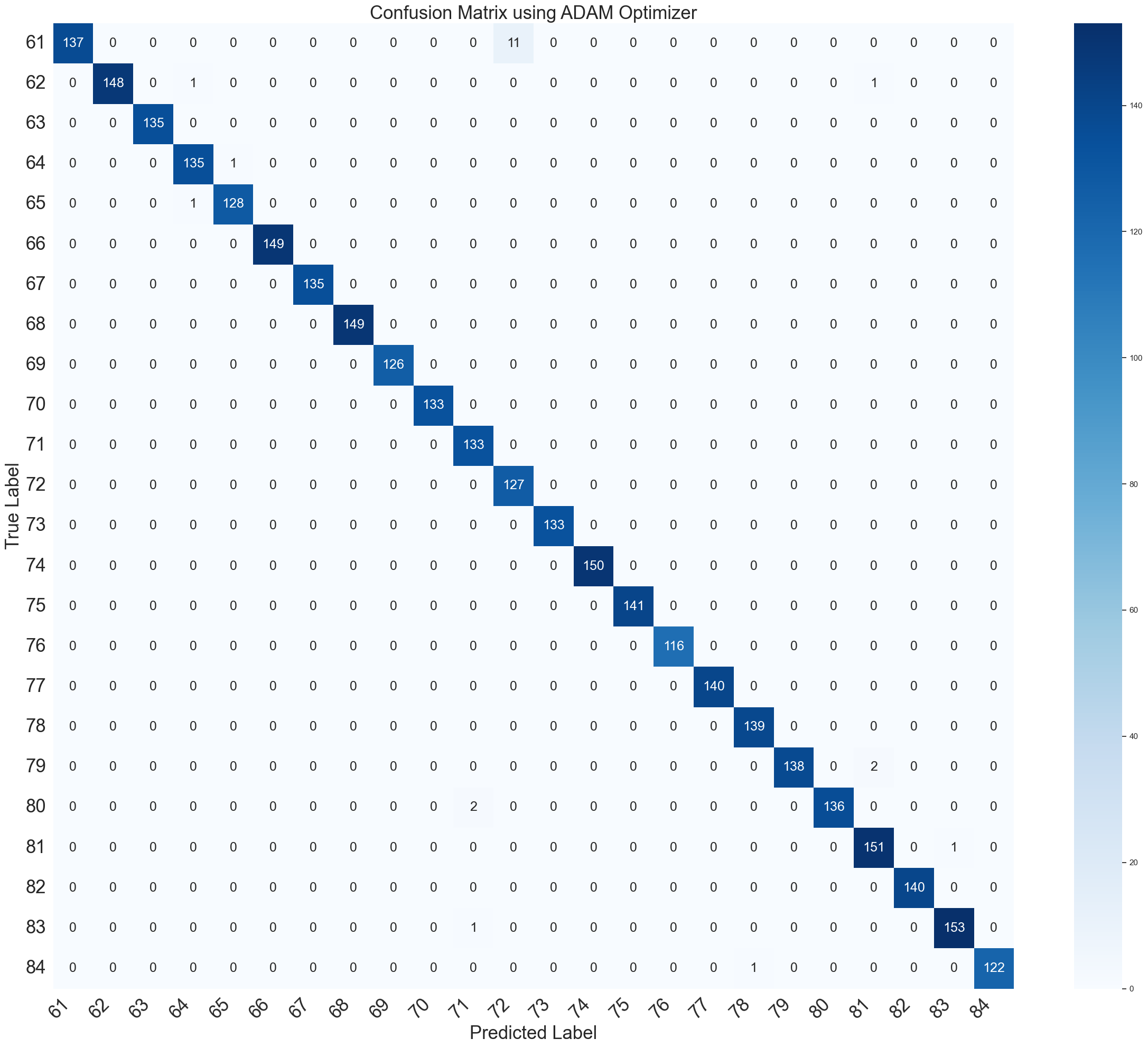


Figure 4.3: Confusion Matrix (Adam)

## The Adam Optimizer Confusion Matrix is a visual representation of the performance of a machine learning model trained using the Adam optimizer. It is a 2x2 matrix that helps us understand how well the model is performing in terms of classification.

## In this matrix, the rows represent the actual classes, while the columns represent the predicted classes. The diagonal elements (top-left to bottom-right) show the number of correct predictions, indicating true positives and true negatives. On the other hand, the off-diagonal elements represent incorrect predictions, including false positives and false negatives.

## A high number of true positives and true negatives in the matrix suggests that the Adam optimizer has been successful in correctly classifying instances. Conversely, an elevated number of false positives and false negatives would indicate misclassifications. Overall, a well-performing Adam optimizer Confusion Matrix should exhibit a strong diagonal with minimal off-diagonal values, signifying the effectiveness of the model in its classification tasks when compared to other optimizers.

## Descriptive Analysis

The scatter plot graphs show validation accuracy and validation loss, the table shows classification report and the matrix table shows confusion matrix. All the graphs represent two metrices, train and validation. The former is described using green curve and the latter using red. The x-axis of the graph is epoch count and the y-axis is accuracy or loss depending on graph.

**Validation Accuracy:** While employing the Adam optimizer, the “Accuracy vs. epoch” graph shows that the training curve is somewhat constant and without any noticeable fluctuations. On the other hand, the validation curve is all over the place at the beginning. From 0-5 epoch, the validation curve takes a dive which suggests noise. These random fluctuations continue until around 11th epoch. After that the curve comes to a smooth plateau. There is a divergence between training and validation curve in 20-25 epoch. In the divergence, train accuracy improves while validation plateau drops ever so little. This may be caused by overfitting. The train accuracy curve reaches peak performance of 1.0 unit at 15th epoch to rest while validation accuracy follows closely.

As for the SGD optimizer scatter plot graph, both the train accuracy and validation accuracy are more constant and gradual. The train curve begins around 0.9 unit and starts gradual ascend, reaching peak at 5th epoch. On the other hand, validation curve maintains a noticeable gap with the train graph. There is a slight decrease around 8th, 9th epoch. Overfitting explains the divergence.

While utilizing no optimizer, the train curve shows promise with its early plateau which reaches peak around 30th epoch. But the validation curve is all over the place with huge fluctuations. This shows that the noise in dataset is insurmountable. Also, the gap between the two graphs points to overfitting problems.

**Validation Loss:** The “Loss vs. Epoch” scatter plot graph of Adam optimizer gives us a somewhat normal train graph. The value decreases with every passing iteration. This shows that the loss is gradually decreasing. The initial half of the validation curve shows huge fluctuations which indicates that there is too much noise due to data variability, optimization algorithm and random initialization of model parameters. The curve becomes consistent on the second half indicating the slowing down of model improvement. During the 15-20 epochs, the graph shows convergence meaning that the model has reached a stable state where further training does not significantly improve its performance.

The SGD optimizer graph puts out a steadier result. Both train and validation curve are gradual in its descent. The validation curve shows a slight alteration that can be due to noise. The whole graph has a divergence pointing to the model is becoming too specialized to the training data, making it perform poorly on unseen data.

As with the validation accuracy graph, the validation loss graph of no optimizer shows heavy curvature shifts throughout the graph. The training acts normally, gradually decreasing, indicating better model performance. But the accuracy curve does not hold its position at all showing that the effect of using none of the optimizers is apparent.

**Classification Report:** For Adam optimizer, F1-score and support score are 0.99 and 3316 respectively. For precision and recall, the macro average and weighted average is of the same value of 0.99.

For SGD optimizer, F1-score is 0.96 through accuracy, macro and weighted average. Support stands at 3316. Precision and recall are 0.97 and 0.96 respectively.

For no optimizer, F1-score has an accuracy of 0.04 and macro average and weighted average is 0.00 for both cases. Support stands at 3316. As for precision, the value is 0.00 for all. And for recall, the value is 0.04 all around.

**Confusion Matrix:** The confusion matrix data are as follows-

* Rows correspond to the actual class labels.
* Columns correspond to the predicted class labels.
* The matrix is 24x24 because it seems to represent a classification task with 24 different classes.
* The diagonal elements (from the top-left to the bottom-right) represent the number of instances where the actual class matches the predicted class. In other words, they show the correct predictions.
* The off-diagonal elements represent the number of instances where the model made incorrect predictions. For example, the element at row 1, column 12 (16) represents the number of instances where the actual class was in the first row, but the model predicted it to be in the 12th column.
* Each row sums up to the total number of instances in the corresponding actual class, while each column sums up to the total number of instances predicted in that class.

**Chapter 5**

# Discussion

In this chapter, the result and findings are thoroughly analyzed and commented on. The first section result analysis contains the overall details of the results and the comparison between the different findings. The analysis is followed by the explanation of said results and findings and why they are what they are. The limitations section contains various issues and limitations faced from the gathered results and some possible solutions to the limitations. In the final discussion,

## Result Analysis

**Validation Accuracy:** Our system utilized three different optimizers and the output clearly shows the difference. From figures 1, 2 and 3 we can clearly notice the difference in model accuracy. Using Adam optimizer puts out the best results. The validation curve starts with a few fluctuations, which is expected due to noise in the data or data variability. In this particular case, the alterations might be the result of smaller batch size. Smaller batch causes the model’s parameters to update more frequently. The fluctuations start at the beginning and continues until 12th iteration. After the initial fluctuations, the curve starts to be more consistent and gradually increases. This plateau begins at 12th iteration and stays consistent until the end. This signifies that the model parameters are getting better at analyzing unseen data. The plateau indicates after a certain number of iterations, the accuracy reaches a stalemate position where more training does not necessarily mean better results or accuracy. This means the model may have already converged to near-optimal solution and additional training doesn't significantly improve its performance. Moving on to figure 2, the graph shows a similarity between the train and validation curve to some degree. The train curve reaches an early peak at only 5th iteration signifying the initial learning phase. The validation curve follows suit but with a slight issue. There is a noticeable divergence between the train and validation curve. Throughout the whole graph this gap continues. The divergence may be the cause of overfitting, The model may have started to memorize the training data rather than learning general patterns. This leads to poor generalization to unseen data, causing a drop in validation accuracy. It also might be the result of high learning rate. A high learning rate can cause the model to overshoot optimal weights and bias values during training, making it harder for the model to converge to a good solution. The complexity of the model also causes the divergence. If your model is too complex for the amount of available data, it's more likely to overfit, leading to divergence in the validation accuracy. Issues with the validation data, such as data leakage or data preprocessing problems, can also lead to divergence in the validation accuracy. Moving no to figure 3 containing validation accuracy graph of no optimizer, the training curve shows a promising result with its gradual ascend and consistent demeanor. But the validation accuracy is inconsistent and its fluctuations are in every quarter. The lack of any optimizer is apparent in the graph. The training comes to a halt around the 38th iteration. This early stopping indicates that the validations accuracy starts to degrade.

**Validation Loss:** The validation loss graph of Adam optimizer showed in figure 1 presents a normal train curve which follows a gradual descent pathway. The validation curve similar to the validation accuracy graph shows fluctuations at the initial process up until 11th iteration. After the initial alterations, the curve evens out into plateau. The alterations in the beginning might be the result of an inappropriate learning rate. A learning rate that is too high might cause the loss to oscillate and fail to converge. Conversely, a learning rate that is too low might result in slow convergence, and the model may get stuck in local minima. In the early stages of training, the model's weights are initialized randomly, and the optimization process may be unstable, causing fluctuations in the loss. As training progresses, the model's weights become better tuned, and the loss should become more stable. Noise could also cause fluctuations. On the other hand, validation loss graph of SGD optimizer shown in figure 2 puts out a more uniform result. There is rarely any fluctuations or dramatic changes in both the curves. But there is a lingering gap between the two curves similar to the validation accuracy graph of the same optimizer. This again may be the cause of overfitting. Overfitting occurs when the model becomes too specialized in fitting the training data, capturing noise rather than meaningful patterns. This leads to poor generalization, causing an increase in validation loss. Lastly, the validation loss graph while using no optimizer is presented in graph 3. The absence of optimizer is very pronounced as the train curve and the validation curve are opposite in nature. Train curve is consistent but the validation curve is shifting rapidly. The noise is almost unbearable and the training comes to an end at 23rd iteration due to early stopping.

**Classification Report:** In the classification report, it is shown that the out of three of the resultants, Adam optimizer result gives out the best performance. The accuracy, macro average and weighted average of the precision, recall and f1-score is 0.99. The precision score 0.99 (or 99%) means that 99% of the positive predictions made by the model are actually correct, and only 1% of them are false positives. In other words, the model is very good at correctly identifying positive cases and has a very low rate of mistakenly classifying negative cases as positive. The recall score of 0.99 (99%) indicates that the model correctly identified 99% of the actual positive cases, and only 1% of the actual positive cases were missed or classified incorrectly as negatives. A high recall score is desirable in situations where it's crucial to minimize false negatives, as it means the model is very good at finding the true positive cases, but it may come at the cost of a higher rate of false positives. An F1-score of 0.99 indicates that the model has an extremely high precision and recall, and it is likely performing very well in terms of both minimizing false positives and false negatives. On the other hand, SGD optimizer result holds the second place having precision of 0.97, recall of 0.96 and f1-score of 0.96. These outputs are close to the outputs of Adam optimizer but not as accurate as them. Lastly, the precision and recall score of no optimizer is 0.00 and 0.04 respectively. This shows the significant drop in accuracy caused by the lack of optimizer. The f1-score is also hampered as accuracy is 0.04 and macro-weighted average is lowly 0.00. This goes to show that the use of optimizers leaves a huge impact on the output of the system. The support score of 3316 in all three outputs does not have any significance except their similarity.

**Confusion Matrix:** The three confusion-matrix provides with the prediction data of Adam, SGD and No Optimizer. Out of the three, Adam optimizer has better prediction outcome. In the other two, the sum of the diagonal data is better for Adam than the other two. The off-diagonal data is also improved in Adam. For example, the row 1, column 12 data is 16 for Adam but 45 for both SGD and No optimizer. This stipulates that prediction inaccuracy is lower in Adam than the other two.

## Comparisons

The primary objective of this research was to create a system that outperforms all the other research outputs done till this point. Let us analyze our results and compare it with other researches.

The following table contains a comparative documentation of all the recent studies available on the related topic –

Table

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Used Model | Dataset | Accuracy | Precision | F1-Score | Support | Recall | References |
| Keras with TensorFlow as backend | BanglaLekha-Isolated | 94.576% (loss value = 0.204) | 0.95 (average) on each class | 0.95 (average) | Not given | 0.95 (average) on each class | [(PDF) Bangla Handwritten Character Recognition using Convolutional Neural Network with Data Augmentation (researchgate.net)](https://www.researchgate.net/publication/333618625_Bangla_Handwritten_Character_Recognition_using_Convolutional_Neural_Network_with_Data_Augmentation) |
| Basic CNN | BanglaLekha-Isolated | Training accuracy = 99.08%  Validation accuracy = 92.25% | Not given | Not given | Not given | Not given | [(PDF) Bangla Handwritten Character Recognition Using Extended Convolutional Neural Network (researchgate.net)](https://www.researchgate.net/publication/350489483_Bangla_Handwritten_Character_Recognition_Using_Extended_Convolutional_Neural_Network) |
| MobileNet V1 Architecture | CMATERdb | 96.56% (validation)  96.46% (validation) | 96.26% (validation set)  96.17% (test set) | Not given | Not given | Not given | [Bangla handwritten character recognition using MobileNet V1 architecture | Ghosh | Bulletin of Electrical Engineering and Informatics (beei.org)](https://www.beei.org/index.php/EEI/article/view/2234/1837) |
| SE-ResNeXt | Mendeley BanglaLekha-Isolated 2 | 99.82% | 97.75% | 97.62% | Not given | 97.63% | [A squeeze and excitation ResNeXt-based deep learning model for Bangla handwritten compound character recognition - ScienceDirect](https://www.sciencedirect.com/science/article/pii/S1319157821000392) |
| KDANet | BanglaLekha-Isolated | 98.10% | Not given | 98.12% | Not given | Not given | [KDANet: Handwritten Character Recognition for Bangla Language using Deep Learning | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/abstract/document/10054708) |
| DCNN with ReLU and  Dropout | CMATERdb | 95.5% | Not given | Not given | Not given | Not given | [Handwritten Isolated Bangla Compound Character Recognition | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/document/8679258) |
| Residual CNN with an attention mechanism (RATNet) | CMATERdb, BanglaLekha-Isolated | 97.79%  96.94%  95.10%  92.91% | Not given | 97.17%  96.74%  94.90%  92.49% | Not given | Not given | [J23\_RATNet\_PostPrint.pdf (unimi.it)](https://air.unimi.it/bitstream/2434/937745/2/J23_RATNet_PostPrint.pdf) |
| Deep CNN | NumtaDB | Training = 99.59%  Validation = 98.57%  Testing = 92.72% | 94.28% | 94.19% | Not given | 94.17% | [Bangla Handwritten Digit Recognition Using Deep CNN for Large and Unbiased Dataset | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/document/8554900) |
| 12-layer CNN | BanglaLekha, Ekush, Custom | 92.48%  97.24%  97.03% | Not given | Not given | Not given | Not given | [(PDF) Handwritten Bengali Alphabets, Compound Characters and Numerals Recognition Using CNN-based Approach (researchgate.net)](https://www.researchgate.net/publication/372337900_Handwritten_Bengali_Alphabets_Compound_Characters_and_Numerals_Recognition_Using_CNN-based_Approach) |
| DConvAENNet | CMATERdb 3.1 | 93.36% | Not given | Not given | Not given | Not given | [Bangla Handwritten Character Recognition Using Deep Convolutional Autoencoder Neural Network | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/document/9333472?fbclid=IwAR16pBGwQPdsIDa91VUuT81CBBu0VBp-UzQ-QzSyyCZ0JOeOfbQLf7aT144) |
| EkushNet | Ekush, CMATERdb | 97.73% (Ekush)  95.01% (CMATERdb) | Not given | Not given | Not given | Not given | [EkushNet: Using Convolutional Neural Network for Bangla Handwritten Recognition - ScienceDirect](https://www.sciencedirect.com/science/article/pii/S1877050918321355) |
| CNN-BiLSTM | CMATERdb 3.1.3.3 | 98.50% | Not given | Not given | Not given | Not given | [Bangla Compound Character Recognition by Combining Deep Convolutional Neural Network with Bidirectional Long Short-Term Memory | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/document/9068817) |
| DCNN and VGG-16 | BanglaLekha-Isolated dataset, CMATERdb | 93.07% | Not given | Not given | Not given | Not given | [Bangla Handwritten Character Recognition Using Convolutional Neural Network | SpringerLink](https://link.springer.com/chapter/10.1007/978-981-19-2347-0_56) |
| CNN | Ekush, BanglaLekha, and NumtaDB | Ekush = 98.36%  BanglaLekha = 96.09% | Given in supplementary pdf | Given in supplementary pdf | Given in supplementary pdf | Given in supplementary pdf | [Applied Sciences | Free Full-Text | BengaliNet: A Low-Cost Novel Convolutional Neural Network for Bengali Handwritten Characters Recognition (mdpi.com)](https://www.mdpi.com/2076-3417/11/15/6845) |
| Deep CNN | CMATERdb 3.1.2 | 98.03% | Not given | Not given | Not given | Not given | [An Automated System for Recognizing Isolated Handwritten Bangla Characters using Deep Convolutional Neural Network | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/document/9431799) |

The following table contains our result in a more focused form –

Table

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Optimizer | Dataset | Accuracy | Precision | F1-Score | Recall | Support |
| Adam | BanglaLekha-Isolated | 99% | 0.99 | 0.99 | 0.99 | 3316 |
| SGD | BanglaLekha-Isolated | 96% | 0.97 | 0.96 | 0.96 | 3316 |
| None | BanglaLekha-Isolated | 4% | 0.00 | 0.04 | 0.04 | 3316 |

**Our Thesis Results:**

* Optimizer: Adam
* Accuracy: 99%
* Precision: 0.99
* F1-Score: 0.99
* Recall: 0.99

**Other Studies on BanglaLekha-Isolated Dataset:**

* + - * 1. Keras with TensorFlow as backend:
* Accuracy: 94.576%
* Precision: 0.95 (average on each class)
* F1-Score: 0.95 (average)
* Recall: 0.95 (average on each class)
  + 1. Basic CNN:
* Training accuracy: 99.08%
* Validation accuracy: 92.25%
  + 1. KDANet:
* Accuracy: 98.10%
* F1-Score: 98.12%
  + 1. SE-ResNeXt:
* Accuracy: 99.82%
* Precision: 97.75%
* F1-Score: 97.62%
* Recall: 97.63%
  + 1. DCNN and VGG-16:
* Accuracy: 93.07%
  + 1. CNN:
* Ekush accuracy: 98.36%
* BanglaLekha accuracy: 96.09%

Now, let's analyze the comparison:

Our thesis results using the Adam optimizer outperform most of the other models in terms of accuracy (99%). This suggests that your model achieved the highest accuracy on the BanglaLekha-Isolated dataset among the listed studies. In terms of precision, your model (0.99) also outperforms other studies, except for the Keras model which has an average precision of 0.95 on each class. Our model's F1-Score (0.99) and Recall (0.99) are also high, indicating that it performs very well in terms of both precision and recall on this dataset. SE-ResNeXt model comes close in terms of accuracy and precision, but our model still has a slightly higher accuracy and precision. Other models, such as the Basic CNN, KDANet, and DCNN and VGG-16, have lower accuracy and performance metrics compared to our model. In summary, our thesis results, using the Adam optimizer, demonstrate superior performance in terms of accuracy, precision, F1-Score, and recall when compared to most of the other studies on the BanglaLekha-Isolated dataset. It appears that our model achieved impressive results on this specific dataset. This clearly indicates that we have achieved our research objective.

## Limitations

As with all the other researches, our particular system has some limitations and issues. These are described as given –

* **Noise:** Noise in a validation accuracy graph refers to fluctuations or irregularities in the validation accuracy values as the model is trained or as epochs progress. There are fluctuations in the initial curve of Adam optimizer and the whole of no optimizer has fluctuations. This indicates noise in the data. Noise fluctuations can happen for different reasons, mainly small datasets. The validation accuracy can be sensitive to individual data points. Minor variations in the data or a small number of misclassified examples can lead to significant accuracy fluctuations. To address this, we can consider using techniques like k-fold cross-validation to get more stable estimates of model performance. A learning rate that is too high can cause the model's training process to oscillate and result in noisy accuracy trends. We may need to adjust the learning rate or use learning rate schedules to find a more stable convergence path. The choice of mini-batch size during training can impact the noise in the validation accuracy. Smaller mini-batch sizes can lead to more significant fluctuations. Experimenting with different batch sizes can help find a balance between stability and training time.
* **Overfitting:** Overfitting in a validation accuracy graph is a common issue that occurs when a machine learning model performs exceptionally well on the training data but poorly on the validation data. This phenomenon is a sign that the model has learned to memorize the training data, capturing noise and outliers, rather than generalizing well to unseen data. Overfitting is a issue in our SGD resultants as there are noticeable gaps between the train curve and validation curve. The overfitting might occur due to the use of small datasets. Using small datasets, the model may have insufficient examples to learn the true underlying patterns. In such cases, the model might resort to memorizing the training data, leading to overfitting. Noisy data may also cause overfitting as seen in the no optimizer output. If the training data contains noise or errors, the model can capture this noise, thinking it represents meaningful patterns. Clean and well-preprocessed data can help reduce the risk of overfitting. In some cases, the model may not have been trained for enough epochs or iterations to generalize well to unseen data. Increasing the training time may help, but it should be balanced to avoid overfitting. Leakage of information might also be blamed for our overfitting. Leakage occurs when the model inadvertently accesses information from the validation or test data during training. This can happen if data preprocessing steps, such as scaling or feature engineering, are applied to the entire dataset without separating training and validation data properly.

**Chapter 6**

# Conclusion & Future Work

In this thesis, we have addressed the crucial challenge of Bangla handwritten character recognition using an ensemble of three deep convolutional neural network (CNN) models: DenseNet121, VGG16, and InceptionV3. The research was driven by the recognition of the vital role of language and communication, with a focus on preserving and enhancing the Bangla language's presence in technology. Our research journey started by curating a dataset of Bangla compound characters, which is essential for training and evaluating our models. We addressed issues such as visual complexity, class imbalance, and licensing to ensure the dataset's quality and accessibility to the community.

To establish a strong baseline, we fine-tuned state-of-the-art deep CNNs, which were originally pretrained on ImageNet, to the Bangla dataset. We explored architectures based on their performance on ImageNet, leveraging their pre-learned weights while tailoring them to Bangla script recognition. The results helped us identify the best individual model based on test accuracy, laying the foundation for our ensemble approach. The core contribution of this research lies in the development of an ensemble model that combines the strengths of three diverse base models. The ensemble model was designed to improve classification accuracy and robustness by promoting diversity and reducing variance and bias. We used a simple late fusion method by concatenating the outputs of the base models, laying the groundwork for more complex fusion techniques in future research. Our experiments explored three optimization options: Adam optimizer, SGD optimizer, and no optimizer. The results unequivocally showed that the Adam optimizer yielded the best performance, followed by the SGD optimizer, while the absence of optimization lagged behind. This empirical evidence underscores the significance of proper optimization in the context of Bangla handwritten character recognition. We analyzed the results comprehensively, employing appropriate classification metrics and visualizations such as confusion matrices, learning curves, and classification reports. These tools provided insights into the model's performance, error patterns, and learning dynamics. In line with open science principles, we have made our dataset, models, and code open source, fostering reproducibility and collaboration within the Bangla language processing community. This step not only facilitates further research but also enhances the impact of our work. By situating our research in the broader context of Bangla optical and handwritten character recognition, we compared our findings to state-of-the-art approaches, identified limitations, and discussed potential real-world applications and societal implications. In summary, this thesis advances the field of Bangla handwritten character recognition by leveraging ensemble learning techniques and deep CNNs. The ensemble model combining DenseNet121, VGG16, and InceptionV3, fine-tuned on the CMATER Bangla isolated character dataset, outperforms individual models in classifying 24 Bangla compound characters. Our research provides a robust methodology and benchmark for Bangla character classification, contributing to the broader goal of preserving and enhancing the Bangla language's presence in technology. While limitations exist, the potential impact on handwriting and printed Bangla OCR systems is substantial, opening doors to future advancements in this domain. While this thesis has made significant strides in the field of Bangla handwritten character recognition using an ensemble of three CNN models (DenseNet121, VGG16, and InceptionV3) and explored various optimization options, there remain several avenues for future research and improvement in this domain. The following are potential areas for future work:

**1. Model Ensemble Enhancement:** The current research focused on a simple ensemble method by concatenating model outputs. Future work could investigate more advanced ensemble techniques, such as weighted averaging, stacking, or boosting, to further improve classification accuracy and robustness.

**2. Architectural Variations:** Exploring different architectures and variations of neural networks tailored specifically for Bangla character recognition could lead to better results. Customized architectures designed with a deep understanding of the Bangla script's intricacies might provide substantial performance gains.

**3. Data Augmentation Strategies:** Further research can be conducted to explore advanced data augmentation techniques specific to Bangla characters. Augmentation strategies that consider the unique characteristics of Bangla script, including ligatures and character variations, could enhance model generalization.

**4. Larger and More Diverse Datasets:** Expanding the dataset size and diversity is essential for improving model performance. Collecting a more extensive and varied dataset of Bangla handwritten characters, encompassing various writing styles and complexities, can lead to better recognition accuracy.

**5. Domain Adaptation:** Investigating domain adaptation techniques to bridge the domain gap between pretrained models (e.g., ImageNet) and Bangla script could be beneficial. Fine-tuning models on a more extensive and diverse Bangla dataset might mitigate the domain shift issue.

**6. Multilingual Recognition:** Extending the research to multilingual character recognition, where the models can recognize characters from multiple languages, including Bangla, can have practical applications in diverse linguistic environments.

**7. Hyperparameter Optimization:** A more comprehensive exploration of hyperparameters, such as learning rates, batch sizes, and weight initializations, could further fine-tune model performance. Additionally, the investigation of learning rate schedules and optimization techniques specific to CNNs for Bangla character recognition is warranted.

**8. Error Analysis and Interpretability:** A deeper understanding of model errors and misclassifications can guide improvements. Techniques for visualizing model attention and decision-making processes can provide insights into why certain characters are challenging to recognize.

**9. Real-Time Recognition:** Adapting the models for real-time recognition on mobile devices or edge computing platforms can broaden the practical applications of Bangla character recognition, such as assisting individuals with visual impairments or enabling efficient data entry.

**10. Deployment and Accessibility:** Developing user-friendly applications or APIs for Bangla character recognition can make the technology accessible to a broader audience and contribute to its adoption in various sectors, including education, government, and business.

**11. Open-Source Contributions:** Continuing the tradition of open sourcing data, models, and code can foster collaboration within the Bangla language processing community, accelerating advancements in the field.

**12. Benchmarking and Evaluation:** Regularly benchmarking the developed models against newer state-of-the-art approaches in Bangla character recognition is essential to ensure that the technology remains competitive and up-to-date.

In conclusion, this thesis has laid the foundation for Bangla handwritten character recognition using deep learning and ensemble techniques. However, the journey towards achieving highly accurate and robust recognition systems for Bangla characters is an ongoing one. Future research efforts should aim to address the aforementioned areas of improvement, ultimately contributing to the accessibility and preservation of the rich cultural and linguistic heritage associated with the Bengali (Bangla) language.

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*End quote goes here*