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Automated Detection of Diabetic Retinopathy Using conventional neural network

Anaam A. Muhamed[a], *, Mohamed I. Shuja, Basman M. Al Nedawe

[a] *Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq. Email: bbc4004@mtu.edu.iq, drshujaa@mtu.edu.iq*

technical Institute of Baquba, Middle Technical University, Diyala, Iraq. Email: *b.alnedawe@mtu.edu.iq*

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ABSTRACT

Convolutional neural networks (CNNs) have emerged as a powerful tool in medical image analysis, enabling automated disease detection with high accuracy. In this study, a CNN-based approach was applied to retinal images to detect diabetic retinopathy, a leading cause of vision impairment in diabetic patients. Traditional detection methods rely on manually defined image features, such as blood vessels or exudates, which can limit diagnostic accuracy and require significant human intervention. These approaches also face challenges in identifying subtle pathological variations due to the complex and diverse visual patterns in retinal images.

The proposed CNN model automatically extracts relevant visual features and classifies retinal images without manual intervention, achieving robust performance in distinguishing between Moderate and No Diabetic Retinopathy cases. Furthermore, the system is designed for potential integration into Internet of Things (IoT) environments, allowing real-time, remote diagnostics and supporting improved healthcare delivery. These results demonstrate the potential of CNNs to enhance automated screening and contribute to more efficient, accurate diabetic retinopathy detection.

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1. INTRODUCTION

Diabetes mellitus is recognized as one of the most prevalent and rapidly increasing chronic diseases worldwide. It constitutes a major global health burden according to the World Health Organization (WHO). Since 1965, numerous research studies have been conducted to improve awareness and promote specific standards for the diagnosis, monitoring, and treatment of diabetes [1]. In diabetes, the human body either fails to produce sufficient insulin to regulate blood sugar levels or cannot effectively utilize the insulin produced. This dysfunction leads to several complications, including kidney disease, cardiovascular disorders, nerve damage, blindness, and damage to blood vessels [2].

The **Internet of Things (IoT)** represents one of the most transformative developments in modern technological history. It enables real-time communication and data exchange between connected devices and systems. **Machine Learning (ML)**, a subset of artificial intelligence, focuses on the development of algorithms that can learn and make predictions based on data [3,4]. As medical data have become increasingly digitized, the role of machine learning has grown significantly in detecting and predicting various diseases. Over the past decade, researchers in both

∗Corresponding author: Anaam Abdull Muhamed

Email addresses: bbc4004@mtu.edu.iq

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medical and machine learning fields have explored numerous approaches for early disease detection and diagnosis within the healthcare sector [5,6].

Recent technological advancements have made it possible to integrate IoT and machine learning in healthcare applications. In clinical environments, this combination can create intelligent and interconnected systems that assist healthcare professionals and patients through continuous monitoring, data analysis, and decision support. IoT technology focuses on gathering information from various sources, while machine learning emphasizes analyzing, enriching, and drawing conclusions from this data. The main goal of IoT is to create a "smart" environment by providing accurate, timely, and context-aware information that supports automated decision-making processes.

Modern lifestyles—characterized by irregular eating habits, poor nutrition, environmental pollution, lack of physical activity, long working hours, and chronic stress—have been identified as major risk factors for developing chronic diseases such as diabetes. Studies indicate that approximately 40% of young adults, middle-aged individuals, and working women in many countries lead sedentary lifestyles that negatively impact their overall health [10]. As a result, integrating IoT and machine learning technologies can provide a valuable framework for healthcare systems to promote early diagnosis, continuous monitoring, and improved management of diabetes, ultimately enhancing the quality of life for patients.

Related Works

Various health systems are devised to facilitate early diagnosis and continuous observation of a patient's health. Various methods has taken in the proposed systems to show the patient health. IoT technology are a great importance in the both medical and technology scale. Over the last few years, a number of studies on IoT based for the medical systems have been made. One method [11] that Still et al. used was machine learning with player heart rate via an IoT system to determine stress beforehand. A pulse sensor is used to determine the heart rate of that patient.

In [12] describes the applicability to work in an Intelligent IoT system on the Machine Learning in healthcare and medicine, illustrated by a building a multi-layer architecture. The fast ability of such an architecture is discovered through a study of ECG based arrhythmia detection, using the deep learning technology and convolutional neural network (CNN. This paper presents an IoT application integrated with machine learning technology to create a next generation of automation system. In [13], they utilize a diabetes data set for experimental purpose.

As a next step, the proposed system has future work for other applications like observations, weather forecasts etc. In [14] the authors presented a system for monitoring real time detection system for the monitoring of health conditions of soldiers in the war in real time which may become lost and are injured in the Warfield. The researchers used different ways for data acquisition. To transmit this real time data from the sensors to the cloud system, they used networking components such as LoRa WAN and ZigBee. For data analysis and predictions on2 ==> 4 warzone environments, the authors used K-Means Clustering algorithm for machine learning.

While K-Mean Clustering generated valuable of early prediction, performance might be improved using density-based clustering algorithms like the DBSCAN because it can also discover clusters of arbitrary for a multiple shape. In [15], the researcher proposed a fuzzy discernibility matrix based on a feature selection Wau, utilizing the parameter K for Motor and EEG Signal Classification. Based on the accuracies of the generation by the Support Vector Machine and Ensemble variations of classifiers, the proposed method outperformed the state-of-the-art methods.

3.propose system

This project aims to detect diabetes by analyzing retinal images using artificial intelligence techniques. A convolutional neural network (CNN) algorithm was used to extract visual features indicative of diabetic retinopathy. Ready-made medical images were taken from a specialized library containing accurate classifications of various disease conditions. After training the model on these images, it was able to distinguish between normal cases and those with varying degrees of the disease. The images were pre-loaded into the system for automatic analysis. The system is integrated within the Internet of Things (IoT) environment, where the analysis results are sent to a medical platform or application for case monitoring. Work is performed on ready-made images. This system provides a smart and accurate way to detect diabetes in its early stages. It also contributes to improving diagnostic processes and supporting automated medical decision-making. The project represents a step towards integrating artificial intelligence with smart healthcare systems.

3.1 Dataset, Hardware and Software

The testing data, which was sourced from the Kaggle website (https://www.kaggle.com) which have over 1000 images, of a 6M pixels. Since those images were then resized and we executed the CNN on the NVIDIA of a moderately GPU with 2880 CUDA cores and also comes with the NVIDIA CUDA, we were able to train with the full dataset. Using this library allowed us to use approximately 15,000 of images to be uploaded on to GPU memory one at a time, the images was disturbed between two classes; Moderate and No_Dr and balanced as two equal classes to prevent over fitting on the model and to provide enough balanced data for testing. The deep learning package used was Keras (http://keras.io/) with the (http://deeplearning.net/software/theano/) as the back-end algorithm because of the documentation to achieve a faster calculation time. A sample of an image could be classified in 0.04 seconds indicating feedback for the patient.

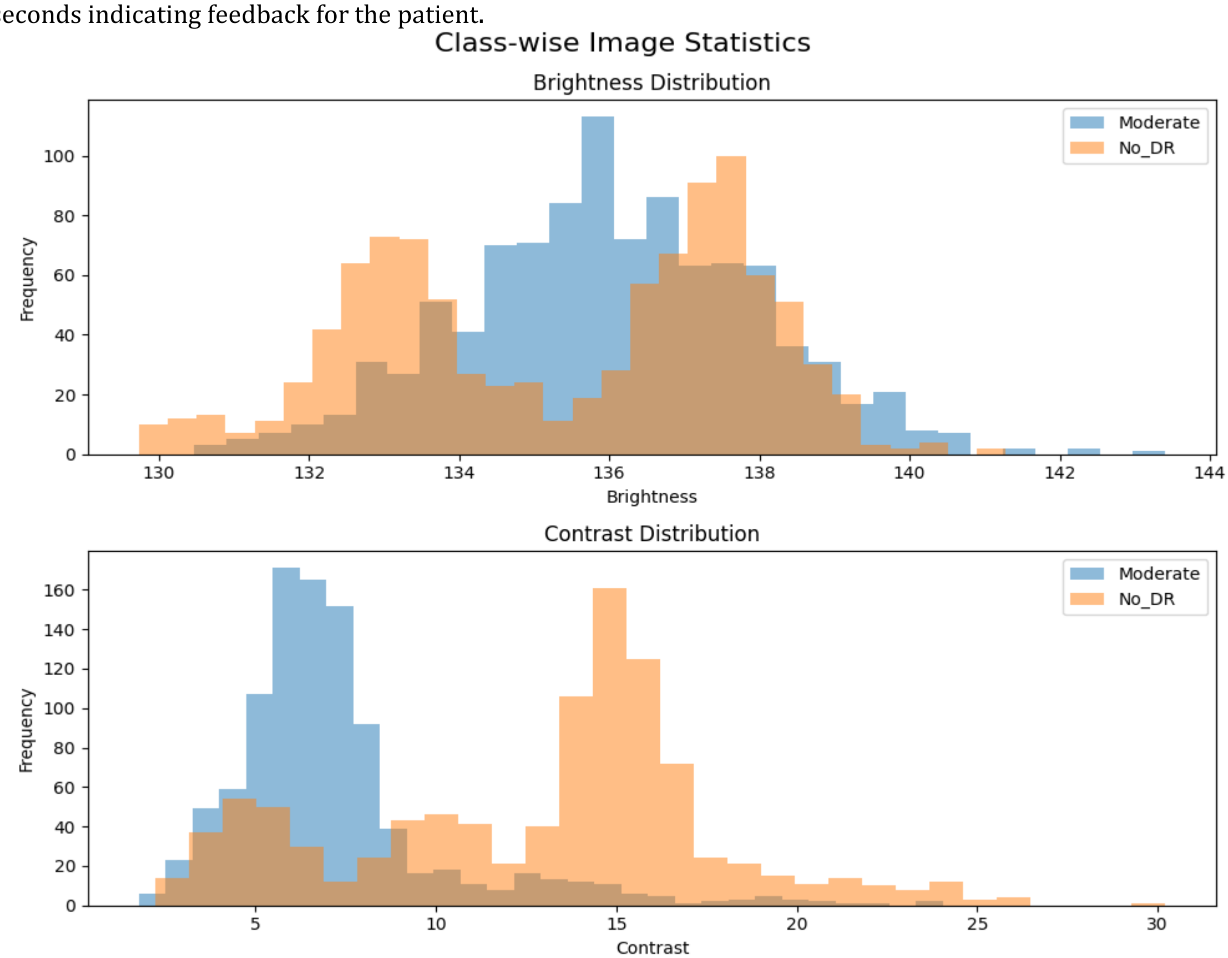


Figure 1: Bright and Contrast Distributions for every class.

3.2. Data Handling

The dataset consisted of a color scale images from multiple patients of different cases, ages, tapers of lighting. This could be affected pixel intensity value with the images themselves, and introduces unwanted parts irrelevant neural network levels. To address it, colors normalization was performed on each of the image's high resolution and of course hence memory size on the GPU. Because of that the dataset was resized to 32x32 pixels, that kept the complex markings we wanted to identifier purpose.

3.2.1 The CNN architecture used in the model

- Layers:
    - 2 Conv2D layers
    - 2 MaxPooling2D layers
    - 1 Flatten layer
    - 1 Dense (hidden) layer
    - 1 Dense (output) layer
      Total: 7 layers
- Filters:
    - First Conv2D: 32 filters
    - Second Conv2D: 64 filters
- Activation Functions:
    - Conv2D layers: relu
    - Dense (hidden) layer: relu
    - Dense (output) layer: softmax
- Epochs:
    - 200 epochs (as set in model.fit)

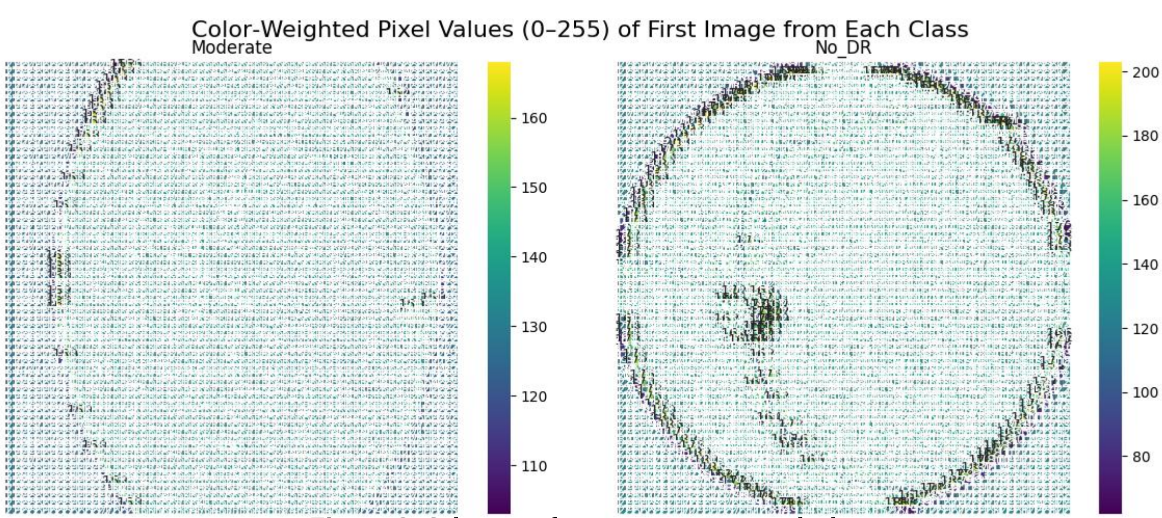


Figure 2: Color map for every image in each class.

3.3. Training and testing

The dataset contains images of patients of various ethnicities, various age groups, camera sources with different lighting, and other factors through the fundus photographs that would affect pixel intensity values in the images and could create unwanted variation that would neither apply to classification levels, nor variants that should be removed. For the purposes of color normalization of the high resolution and high memory, and the subsequent resizing of the dataset to 32x32 pixels to include some of the complex markings we wanted to identify, as well to fully meet the memory limits of the NVIDIA K40c. Below the flow chart of the testing mechanic of the model, tabel 1.The results reveal that while the CNN-based model was capable of learning from the data, its performance was hindered by over fitting, data limitations, and potential architectural constraints. Future iterations of the system should incorporate advanced techniques, including transfer learning, hyper parameter optimization, and dataset augmentation, to enhance its predictive accuracy and generalization ability. Average Training Results After All Epochs:

Average Accuracy: 0.9664

Average Val Accuracy: 0.4884

Average Loss: 0.0985

Average Val Loss: 0.84178

3.3.1 Epoch-wise Training Results:

Epoch 001 - Accuracy: 0.3748, Val Accuracy: 0.4559, Loss: 1.6078, Val Loss: 1.4285

Epoch 002 - Accuracy: 0.4854, Val Accuracy: 0.4906, Loss: 1.3556, Val Loss: 1.3371

Epoch 003 - Accuracy: 0.5359, Val Accuracy: 0.4930, Loss: 1.2310, Val Loss: 1.3327

Epoch 004 - Accuracy: 0.5783, Val Accuracy: 0.4923, Loss: 1.1247, Val Loss: 1.3320

Epoch 005 - Accuracy: 0.6216, Val Accuracy: 0.5223, Loss: 1.0148, Val Loss: 1.3400

Epoch 006 - Accuracy: 0.6668, Val Accuracy: 0.5240, Loss: 0.8986, Val Loss: 1.4007

Epoch 007 - Accuracy: 0.7079, Val Accuracy: 0.5148, Loss: 0.7935, Val Loss: 1.4205

Epoch 008 - Accuracy: 0.7554, Val Accuracy: 0.5132, Loss: 0.6809, Val Loss: 1.5899

Epoch 009 - Accuracy: 0.7917, Val Accuracy: 0.5010, Loss: 0.5785, Val Loss: 1.7307

Epoch 010 - Accuracy: 0.8278, Val Accuracy: 0.5192, Loss: 0.4855, Val Loss: 1.9782

Epoch 011 - Accuracy: 0.8589, Val Accuracy: 0.5063, Loss: 0.3971, Val Loss: 2.1667

Epoch 012 - Accuracy: 0.8875, Val Accuracy: 0.4866, Loss: 0.3258, Val Loss: 2.3934

Epoch 013 - Accuracy: 0.9050, Val Accuracy: 0.4958, Loss: 0.2727, Val Loss: 2.5601

Epoch 014 - Accuracy: 0.9206, Val Accuracy: 0.4972, Loss: 0.2280, Val Loss: 2.9610

Epoch 015 - Accuracy: 0.9295, Val Accuracy: 0.4969, Loss: 0.2028, Val Loss: 3.1889

Epoch 016 - Accuracy: 0.9450, Val Accuracy: 0.5002, Loss: 0.1633, Val Loss: 3.5926

Epoch 017 - Accuracy: 0.9480, Val Accuracy: 0.4948, Loss: 0.1541, Val Loss: 3.5463

Epoch 018 - Accuracy: 0.9543, Val Accuracy: 0.4826, Loss: 0.1400, Val Loss: 3.7018

Epoch 019 - Accuracy: 0.9534, Val Accuracy: 0.4899, Loss: 0.1401, Val Loss: 3.9662

Epoch 020 - Accuracy: 0.9645, Val Accuracy: 0.4885, Loss: 0.1117, Val Loss: 4.0891

Epoch 021 - Accuracy: 0.9597, Val Accuracy: 0.4897, Loss: 0.1195, Val Loss: 4.4011

Epoch 022 - Accuracy: 0.9643, Val Accuracy: 0.4923, Loss: 0.1089, Val Loss: 4.4955

Epoch 023 - Accuracy: 0.9686, Val Accuracy: 0.4977, Loss: 0.0994, Val Loss: 4.5663

Epoch 024 - Accuracy: 0.9706, Val Accuracy: 0.4902, Loss: 0.0947, Val Loss: 4.8732

Epoch 025 - Accuracy: 0.9687, Val Accuracy: 0.5049, Loss: 0.0962, Val Loss: 5.0345

Epoch 026 - Accuracy: 0.9727, Val Accuracy: 0.4923, Loss: 0.0842, Val Loss: 5.0208

Epoch 027 - Accuracy: 0.9680, Val Accuracy: 0.4941, Loss: 0.0991, Val Loss: 5.2314

Epoch 028 - Accuracy: 0.9770, Val Accuracy: 0.4943, Loss: 0.0758, Val Loss: 5.3381

Epoch 029 - Accuracy: 0.9731, Val Accuracy: 0.4930, Loss: 0.0867, Val Loss: 5.4018

Epoch 030 - Accuracy: 0.9737, Val Accuracy: 0.4836, Loss: 0.0836, Val Loss: 5.4353

Epoch 031 - Accuracy: 0.9744, Val Accuracy: 0.4826, Loss: 0.0773, Val Loss: 5.7518

Epoch 032 - Accuracy: 0.9772, Val Accuracy: 0.4866, Loss: 0.0721, Val Loss: 5.8687

Epoch 033 - Accuracy: 0.9755, Val Accuracy: 0.4842, Loss: 0.0828, Val Loss: 5.7429

Epoch 034 - Accuracy: 0.9764, Val Accuracy: 0.4916, Loss: 0.0740, Val Loss: 5.7139

Epoch 035 - Accuracy: 0.9749, Val Accuracy: 0.4922, Loss: 0.0807, Val Loss: 5.6780

Epoch 036 - Accuracy: 0.9775, Val Accuracy: 0.4840, Loss: 0.0763, Val Loss: 6.0438

Epoch 037 - Accuracy: 0.9766, Val Accuracy: 0.4915, Loss: 0.0726, Val Loss: 6.2590

Epoch 038 - Accuracy: 0.9804, Val Accuracy: 0.4836, Loss: 0.0635, Val Loss: 6.0061

Epoch 039 - Accuracy: 0.9787, Val Accuracy: 0.4896, Loss: 0.0685, Val Loss: 6.3571

Epoch 040 - Accuracy: 0.9783, Val Accuracy: 0.4922, Loss: 0.0732, Val Loss: 6.3705

Epoch 041 - Accuracy: 0.9812, Val Accuracy: 0.4854, Loss: 0.0617, Val Loss: 6.3249

Epoch 042 - Accuracy: 0.9801, Val Accuracy: 0.4796, Loss: 0.0645, Val Loss: 6.5636

Epoch 043 - Accuracy: 0.9776, Val Accuracy: 0.4859, Loss: 0.0751, Val Loss: 6.7005

Epoch 044 - Accuracy: 0.9829, Val Accuracy: 0.4850, Loss: 0.0572, Val Loss: 6.5337

Epoch 045 - Accuracy: 0.9812, Val Accuracy: 0.4915, Loss: 0.0609, Val Loss: 6.5980

Epoch 046 - Accuracy: 0.9814, Val Accuracy: 0.4798, Loss: 0.0603, Val Loss: 6.3912

Epoch 047 - Accuracy: 0.9809, Val Accuracy: 0.4880, Loss: 0.0647, Val Loss: 6.3972

Epoch 048 - Accuracy: 0.9827, Val Accuracy: 0.4979, Loss: 0.0546, Val Loss: 7.0155

Epoch 049 - Accuracy: 0.9798, Val Accuracy: 0.5014, Loss: 0.0627, Val Loss: 6.7211

Epoch 050 - Accuracy: 0.9835, Val Accuracy: 0.4899, Loss: 0.0591, Val Loss: 7.0036

Epoch 051 - Accuracy: 0.9831, Val Accuracy: 0.4744, Loss: 0.0596, Val Loss: 6.6916

Epoch 052 - Accuracy: 0.9764, Val Accuracy: 0.4869, Loss: 0.0779, Val Loss: 7.0707

Epoch 053 - Accuracy: 0.9851, Val Accuracy: 0.4889, Loss: 0.0450, Val Loss: 7.0787

Epoch 054 - Accuracy: 0.9793, Val Accuracy: 0.4889, Loss: 0.0660, Val Loss: 7.1500

Epoch 055 - Accuracy: 0.9827, Val Accuracy: 0.4906, Loss: 0.0561, Val Loss: 7.3179

Epoch 056 - Accuracy: 0.9846, Val Accuracy: 0.4789, Loss: 0.0519, Val Loss: 7.4684

Epoch 057 - Accuracy: 0.9838, Val Accuracy: 0.4760, Loss: 0.0517, Val Loss: 6.9117

Epoch 058 - Accuracy: 0.9829, Val Accuracy: 0.4836, Loss: 0.0560, Val Loss: 7.0662

Epoch 059 - Accuracy: 0.9821, Val Accuracy: 0.4916, Loss: 0.0580, Val Loss: 7.6889

Epoch 060 - Accuracy: 0.9862, Val Accuracy: 0.4887, Loss: 0.0431, Val Loss: 7.5420

Epoch 061 - Accuracy: 0.9831, Val Accuracy: 0.4779, Loss: 0.0569, Val Loss: 7.0250

Epoch 062 - Accuracy: 0.9833, Val Accuracy: 0.5010, Loss: 0.0527, Val Loss: 7.5512

Epoch 063 - Accuracy: 0.9846, Val Accuracy: 0.4742, Loss: 0.0503, Val Loss: 7.4659

Epoch 064 - Accuracy: 0.9866, Val Accuracy: 0.4899, Loss: 0.0466, Val Loss: 7.7688

Epoch 065 - Accuracy: 0.9858, Val Accuracy: 0.4925, Loss: 0.0495, Val Loss: 7.5589

Epoch 066 - Accuracy: 0.9862, Val Accuracy: 0.4899, Loss: 0.0461, Val Loss: 7.8455

Epoch 067 - Accuracy: 0.9858, Val Accuracy: 0.4882, Loss: 0.0487, Val Loss: 7.5719

Epoch 068 - Accuracy: 0.9860, Val Accuracy: 0.4878, Loss: 0.0463, Val Loss: 8.4911

Epoch 069 - Accuracy: 0.9852, Val Accuracy: 0.4744, Loss: 0.0504, Val Loss: 7.8136

Epoch 070 - Accuracy: 0.9845, Val Accuracy: 0.4927, Loss: 0.0511, Val Loss: 8.0655

Epoch 071 - Accuracy: 0.9869, Val Accuracy: 0.4852, Loss: 0.0451, Val Loss: 8.1516

Epoch 072 - Accuracy: 0.9852, Val Accuracy: 0.4784, Loss: 0.0495, Val Loss: 7.8587

Epoch 073 - Accuracy: 0.9850, Val Accuracy: 0.4890, Loss: 0.0519, Val Loss: 8.0079

Epoch 074 - Accuracy: 0.9857, Val Accuracy: 0.4896, Loss: 0.0489, Val Loss: 8.0228

Epoch 075 - Accuracy: 0.9848, Val Accuracy: 0.4765, Loss: 0.0536, Val Loss: 7.3651

Epoch 076 - Accuracy: 0.9882, Val Accuracy: 0.4857, Loss: 0.0397, Val Loss: 8.0811

Epoch 077 - Accuracy: 0.9851, Val Accuracy: 0.4906, Loss: 0.0490, Val Loss: 8.6084

Epoch 078 - Accuracy: 0.9866, Val Accuracy: 0.4852, Loss: 0.0420, Val Loss: 8.1106

Epoch 079 - Accuracy: 0.9882, Val Accuracy: 0.4815, Loss: 0.0380, Val Loss: 8.4238

Epoch 080 - Accuracy: 0.9864, Val Accuracy: 0.4925, Loss: 0.0465, Val Loss: 8.7952

Epoch 081 - Accuracy: 0.9851, Val Accuracy: 0.4727, Loss: 0.0527, Val Loss: 8.0612

Epoch 082 - Accuracy: 0.9891, Val Accuracy: 0.4814, Loss: 0.0336, Val Loss: 8.3535

Epoch 083 - Accuracy: 0.9857, Val Accuracy: 0.4758, Loss: 0.0467, Val Loss: 8.5441

Epoch 084 - Accuracy: 0.9837, Val Accuracy: 0.4869, Loss: 0.0523, Val Loss: 8.4533

Epoch 085 - Accuracy: 0.9906, Val Accuracy: 0.4866, Loss: 0.0294, Val Loss: 8.1767

Epoch 086 - Accuracy: 0.9852, Val Accuracy: 0.4862, Loss: 0.0484, Val Loss: 8.3205

Epoch 087 - Accuracy: 0.9881, Val Accuracy: 0.4897, Loss: 0.0391, Val Loss: 8.8808

Epoch 088 - Accuracy: 0.9889, Val Accuracy: 0.4829, Loss: 0.0409, Val Loss: 8.5767

Epoch 089 - Accuracy: 0.9872, Val Accuracy: 0.4845, Loss: 0.0419, Val Loss: 8.7976

Epoch 090 - Accuracy: 0.9887, Val Accuracy: 0.4789, Loss: 0.0385, Val Loss: 8.3361

Epoch 091 - Accuracy: 0.9864, Val Accuracy: 0.4847, Loss: 0.0439, Val Loss: 8.9113

Epoch 092 - Accuracy: 0.9899, Val Accuracy: 0.4887, Loss: 0.0335, Val Loss: 8.6794

Epoch 093 - Accuracy: 0.9893, Val Accuracy: 0.4882, Loss: 0.0377, Val Loss: 8.4522

Epoch 094 - Accuracy: 0.9854, Val Accuracy: 0.4934, Loss: 0.0480, Val Loss: 9.0693

Epoch 095 - Accuracy: 0.9879, Val Accuracy: 0.4918, Loss: 0.0394, Val Loss: 9.0683

Epoch 096 - Accuracy: 0.9882, Val Accuracy: 0.4873, Loss: 0.0441, Val Loss: 8.6143

Epoch 097 - Accuracy: 0.9911, Val Accuracy: 0.4862, Loss: 0.0308, Val Loss: 8.9517

Epoch 098 - Accuracy: 0.9864, Val Accuracy: 0.4956, Loss: 0.0491, Val Loss: 8.7922

Epoch 099 - Accuracy: 0.9899, Val Accuracy: 0.4850, Loss: 0.0362, Val Loss: 8.6878

Epoch 100 - Accuracy: 0.9870, Val Accuracy: 0.4871, Loss: 0.0456, Val Loss: 8.6895

Epoch 101 - Accuracy: 0.9902, Val Accuracy: 0.4908, Loss: 0.0299, Val Loss: 9.0300

Epoch 102 - Accuracy: 0.9864, Val Accuracy: 0.4885, Loss: 0.0442, Val Loss: 9.0151

Epoch 103 - Accuracy: 0.9880, Val Accuracy: 0.4882, Loss: 0.0406, Val Loss: 9.1591

Epoch 104 - Accuracy: 0.9872, Val Accuracy: 0.4997, Loss: 0.0441, Val Loss: 9.3090

Epoch 105 - Accuracy: 0.9903, Val Accuracy: 0.4878, Loss: 0.0331, Val Loss: 9.0998

Epoch 106 - Accuracy: 0.9876, Val Accuracy: 0.4868, Loss: 0.0431, Val Loss: 8.6185

Epoch 107 - Accuracy: 0.9892, Val Accuracy: 0.4979, Loss: 0.0361, Val Loss: 9.4131

Epoch 108 - Accuracy: 0.9885, Val Accuracy: 0.4948, Loss: 0.0391, Val Loss: 8.8807

Epoch 109 - Accuracy: 0.9920, Val Accuracy: 0.5021, Loss: 0.0269, Val Loss: 9.1985

Epoch 110 - Accuracy: 0.9869, Val Accuracy: 0.4788, Loss: 0.0447, Val Loss: 9.2709

Epoch 111 - Accuracy: 0.9875, Val Accuracy: 0.4967, Loss: 0.0425, Val Loss: 9.0875

Epoch 112 - Accuracy: 0.9905, Val Accuracy: 0.4861, Loss: 0.0328, Val Loss: 8.9586

Epoch 113 - Accuracy: 0.9891, Val Accuracy: 0.4970, Loss: 0.0364, Val Loss: 9.3715

Epoch 114 - Accuracy: 0.9932, Val Accuracy: 0.4939, Loss: 0.0228, Val Loss: 9.2416

Epoch 115 - Accuracy: 0.9873, Val Accuracy: 0.4864, Loss: 0.0406, Val Loss: 8.9569

Epoch 116 - Accuracy: 0.9896, Val Accuracy: 0.4852, Loss: 0.0338, Val Loss: 9.5628

Epoch 117 - Accuracy: 0.9887, Val Accuracy: 0.4916, Loss: 0.0371, Val Loss: 10.0315

Epoch 118 - Accuracy: 0.9877, Val Accuracy: 0.4995, Loss: 0.0440, Val Loss: 9.2710

Epoch 119 - Accuracy: 0.9907, Val Accuracy: 0.4956, Loss: 0.0296, Val Loss: 9.3520

Epoch 120 - Accuracy: 0.9915, Val Accuracy: 0.4927, Loss: 0.0300, Val Loss: 9.3258

Epoch 121 - Accuracy: 0.9899, Val Accuracy: 0.4892, Loss: 0.0325, Val Loss: 9.9391

Epoch 122 - Accuracy: 0.9909, Val Accuracy: 0.4876, Loss: 0.0296, Val Loss: 9.8988

Epoch 123 - Accuracy: 0.9891, Val Accuracy: 0.4916, Loss: 0.0365, Val Loss: 9.8521

Epoch 124 - Accuracy: 0.9886, Val Accuracy: 0.4981, Loss: 0.0368, Val Loss: 10.0322

Epoch 125 - Accuracy: 0.9907, Val Accuracy: 0.4749, Loss: 0.0325, Val Loss: 9.4751

Epoch 126 - Accuracy: 0.9914, Val Accuracy: 0.4915, Loss: 0.0292, Val Loss: 9.4677

Epoch 127 - Accuracy: 0.9904, Val Accuracy: 0.4883, Loss: 0.0322, Val Loss: 9.6698

Epoch 128 - Accuracy: 0.9894, Val Accuracy: 0.4873, Loss: 0.0360, Val Loss: 9.7073

Epoch 129 - Accuracy: 0.9909, Val Accuracy: 0.4889, Loss: 0.0322, Val Loss: 9.2921

Epoch 130 - Accuracy: 0.9925, Val Accuracy: 0.4897, Loss: 0.0232, Val Loss: 9.9198

Epoch 131 - Accuracy: 0.9884, Val Accuracy: 0.4892, Loss: 0.0434, Val Loss: 10.2699

Epoch 132 - Accuracy: 0.9930, Val Accuracy: 0.4871, Loss: 0.0253, Val Loss: 9.8526

Epoch 133 - Accuracy: 0.9904, Val Accuracy: 0.4855, Loss: 0.0372, Val Loss: 9.7971

Epoch 134 - Accuracy: 0.9918, Val Accuracy: 0.4845, Loss: 0.0271, Val Loss: 10.2458

Epoch 135 - Accuracy: 0.9892, Val Accuracy: 0.4838, Loss: 0.0354, Val Loss: 9.9206

Epoch 136 - Accuracy: 0.9895, Val Accuracy: 0.4883, Loss: 0.0329, Val Loss: 9.7883

Epoch 137 - Accuracy: 0.9925, Val Accuracy: 0.4873, Loss: 0.0253, Val Loss: 10.0541

Epoch 138 - Accuracy: 0.9894, Val Accuracy: 0.4873, Loss: 0.0372, Val Loss: 10.5311

Epoch 139 - Accuracy: 0.9909, Val Accuracy: 0.4847, Loss: 0.0331, Val Loss: 10.6440

Epoch 140 - Accuracy: 0.9920, Val Accuracy: 0.4894, Loss: 0.0307, Val Loss: 9.9529

Epoch 141 - Accuracy: 0.9894, Val Accuracy: 0.4817, Loss: 0.0313, Val Loss: 9.8226

Epoch 142 - Accuracy: 0.9911, Val Accuracy: 0.4909, Loss: 0.0305, Val Loss: 10.7301

Epoch 143 - Accuracy: 0.9906, Val Accuracy: 0.4913, Loss: 0.0331, Val Loss: 10.3141

Epoch 144 - Accuracy: 0.9927, Val Accuracy: 0.4859, Loss: 0.0251, Val Loss: 10.6820

Epoch 145 - Accuracy: 0.9905, Val Accuracy: 0.4840, Loss: 0.0351, Val Loss: 10.2249

Epoch 146 - Accuracy: 0.9904, Val Accuracy: 0.4842, Loss: 0.0329, Val Loss: 10.6389

Epoch 147 - Accuracy: 0.9917, Val Accuracy: 0.4922, Loss: 0.0260, Val Loss: 10.5103

Epoch 148 - Accuracy: 0.9903, Val Accuracy: 0.4899, Loss: 0.0329, Val Loss: 10.8578

Epoch 149 - Accuracy: 0.9916, Val Accuracy: 0.4956, Loss: 0.0258, Val Loss: 11.3793

Epoch 150 - Accuracy: 0.9891, Val Accuracy: 0.4862, Loss: 0.0360, Val Loss: 10.6478

Epoch 151 - Accuracy: 0.9927, Val Accuracy: 0.4734, Loss: 0.0250, Val Loss: 10.8053

Epoch 152 - Accuracy: 0.9925, Val Accuracy: 0.4791, Loss: 0.0257, Val Loss: 10.4735

Epoch 153 - Accuracy: 0.9903, Val Accuracy: 0.4829, Loss: 0.0333, Val Loss: 10.7908

Epoch 154 - Accuracy: 0.9908, Val Accuracy: 0.4861, Loss: 0.0320, Val Loss: 11.0190

Epoch 155 - Accuracy: 0.9907, Val Accuracy: 0.4902, Loss: 0.0342, Val Loss: 10.7763

Epoch 156 - Accuracy: 0.9904, Val Accuracy: 0.4774, Loss: 0.0354, Val Loss: 10.6764

Epoch 157 - Accuracy: 0.9934, Val Accuracy: 0.4887, Loss: 0.0182, Val Loss: 10.8635

Epoch 158 - Accuracy: 0.9891, Val Accuracy: 0.4848, Loss: 0.0358, Val Loss: 11.2426

Epoch 159 - Accuracy: 0.9912, Val Accuracy: 0.4824, Loss: 0.0311, Val Loss: 10.7722

Epoch 160 - Accuracy: 0.9916, Val Accuracy: 0.4728, Loss: 0.0299, Val Loss: 10.3893

Epoch 161 - Accuracy: 0.9904, Val Accuracy: 0.4871, Loss: 0.0358, Val Loss: 11.5223

Epoch 162 - Accuracy: 0.9912, Val Accuracy: 0.4882, Loss: 0.0293, Val Loss: 11.0676

Epoch 163 - Accuracy: 0.9919, Val Accuracy: 0.4833, Loss: 0.0250, Val Loss: 10.4516

Epoch 164 - Accuracy: 0.9917, Val Accuracy: 0.4890, Loss: 0.0302, Val Loss: 11.8600

Epoch 165 - Accuracy: 0.9924, Val Accuracy: 0.4812, Loss: 0.0259, Val Loss: 10.6850

Epoch 166 - Accuracy: 0.9902, Val Accuracy: 0.4911, Loss: 0.0348, Val Loss: 11.4148

Epoch 167 - Accuracy: 0.9929, Val Accuracy: 0.4835, Loss: 0.0237, Val Loss: 11.6688

Epoch 168 - Accuracy: 0.9891, Val Accuracy: 0.4843, Loss: 0.0457, Val Loss: 11.3410

Epoch 169 - Accuracy: 0.9928, Val Accuracy: 0.4824, Loss: 0.0223, Val Loss: 11.0391

Epoch 170 - Accuracy: 0.9933, Val Accuracy: 0.4828, Loss: 0.0278, Val Loss: 10.5463

Epoch 171 - Accuracy: 0.9923, Val Accuracy: 0.4781, Loss: 0.0236, Val Loss: 11.0709

Epoch 172 - Accuracy: 0.9923, Val Accuracy: 0.4934, Loss: 0.0252, Val Loss: 11.8636

Epoch 173 - Accuracy: 0.9902, Val Accuracy: 0.4805, Loss: 0.0326, Val Loss: 10.9616

Epoch 174 - Accuracy: 0.9911, Val Accuracy: 0.4808, Loss: 0.0306, Val Loss: 11.1233

Epoch 175 - Accuracy: 0.9943, Val Accuracy: 0.4890, Loss: 0.0197, Val Loss: 11.4193

Epoch 176 - Accuracy: 0.9907, Val Accuracy: 0.4836, Loss: 0.0310, Val Loss: 10.9490

Epoch 177 - Accuracy: 0.9935, Val Accuracy: 0.4946, Loss: 0.0213, Val Loss: 11.7212

Epoch 178 - Accuracy: 0.9926, Val Accuracy: 0.4936, Loss: 0.0279, Val Loss: 11.1060

Epoch 179 - Accuracy: 0.9914, Val Accuracy: 0.4848, Loss: 0.0295, Val Loss: 11.9506

Epoch 180 - Accuracy: 0.9921, Val Accuracy: 0.4807, Loss: 0.0257, Val Loss: 11.6073

Epoch 181 - Accuracy: 0.9904, Val Accuracy: 0.4788, Loss: 0.0355, Val Loss: 11.4295

Epoch 182 - Accuracy: 0.9911, Val Accuracy: 0.4913, Loss: 0.0314, Val Loss: 11.2897

Epoch 183 - Accuracy: 0.9930, Val Accuracy: 0.4897, Loss: 0.0254, Val Loss: 11.8960

Epoch 184 - Accuracy: 0.9924, Val Accuracy: 0.4807, Loss: 0.0270, Val Loss: 11.8203

Epoch 185 - Accuracy: 0.9921, Val Accuracy: 0.4880, Loss: 0.0279, Val Loss: 11.9160

Epoch 186 - Accuracy: 0.9930, Val Accuracy: 0.4883, Loss: 0.0290, Val Loss: 11.8913

Epoch 187 - Accuracy: 0.9920, Val Accuracy: 0.4814, Loss: 0.0290, Val Loss: 11.2062

Epoch 188 - Accuracy: 0.9904, Val Accuracy: 0.4812, Loss: 0.0346, Val Loss: 11.2958

Epoch 189 - Accuracy: 0.9932, Val Accuracy: 0.4896, Loss: 0.0233, Val Loss: 11.6362

Epoch 190 - Accuracy: 0.9934, Val Accuracy: 0.4930, Loss: 0.0207, Val Loss: 12.0616

Epoch 191 - Accuracy: 0.9900, Val Accuracy: 0.4915, Loss: 0.0338, Val Loss: 12.3472

Epoch 192 - Accuracy: 0.9917, Val Accuracy: 0.4943, Loss: 0.0300, Val Loss: 11.6424

Epoch 193 - Accuracy: 0.9924, Val Accuracy: 0.4909, Loss: 0.0256, Val Loss: 11.5664

Epoch 194 - Accuracy: 0.9924, Val Accuracy: 0.4864, Loss: 0.0269, Val Loss: 11.7464

Epoch 195 - Accuracy: 0.9926, Val Accuracy: 0.4842, Loss: 0.0261, Val Loss: 12.0686

Epoch 196 - Accuracy: 0.9929, Val Accuracy: 0.4894, Loss: 0.0259, Val Loss: 11.8587

Epoch 197 - Accuracy: 0.9922, Val Accuracy: 0.4883, Loss: 0.0307, Val Loss: 11.8063

Epoch 198 - Accuracy: 0.9936, Val Accuracy: 0.4869, Loss: 0.0208, Val Loss: 12.3902

Epoch 199 - Accuracy: 0.9914, Val Accuracy: 0.4848, Loss: 0.0333, Val Loss: 12.1660

Epoch 200 - Accuracy: 0.9922, Val Accuracy: 0.4796, Loss: 0.0277, Val Loss: 12.2035

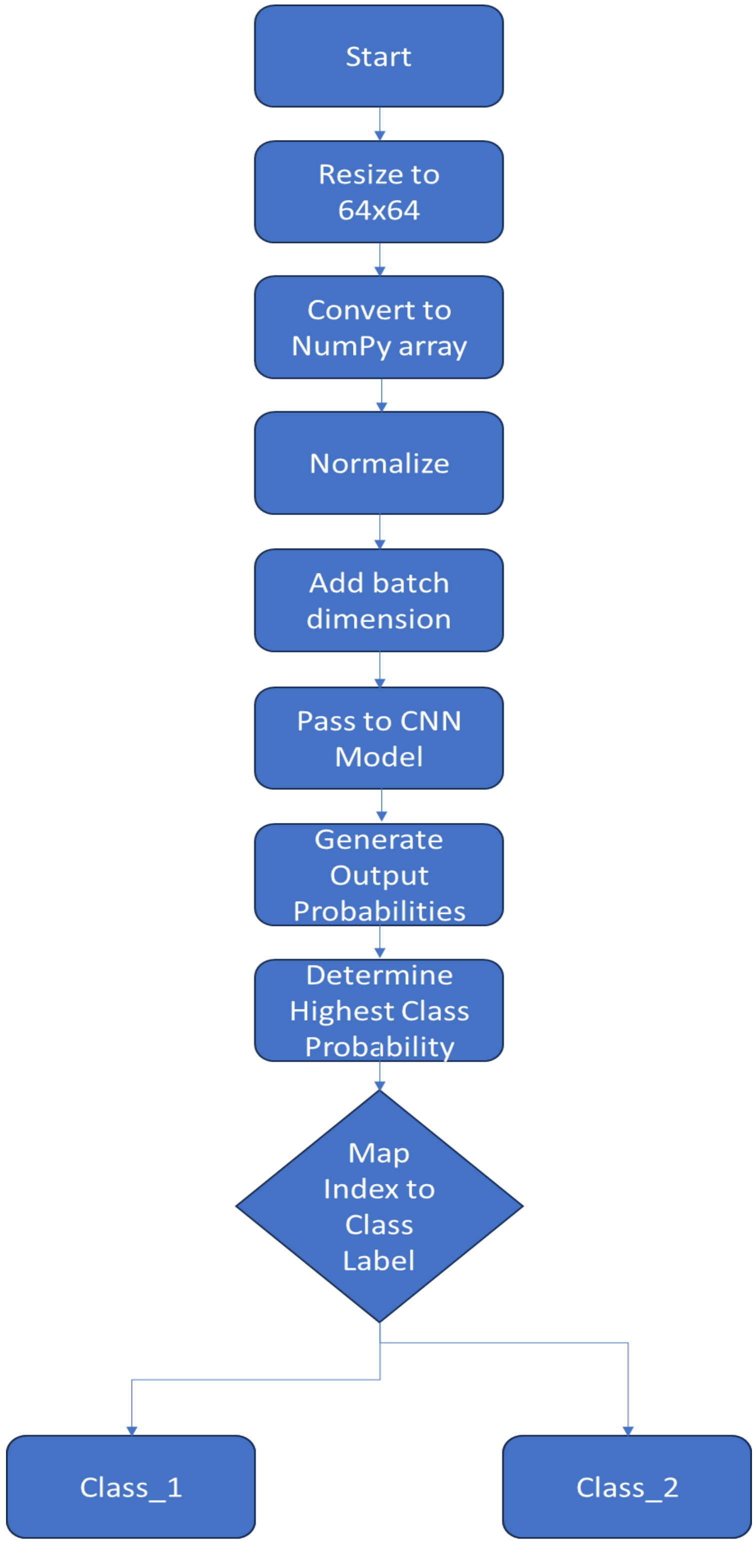


Figure 3: Flow chart of the use of the CNN trained model

3.4 Work Flow for the IOT system

The system uses Raspberry pi 5 (4Gb) version, kali Linux distribution for the server hardware. The website front end use HTML, CSS and Java Script. For the backend uses flask module integrated into the python app. The figure 1 show the work flow of the process.

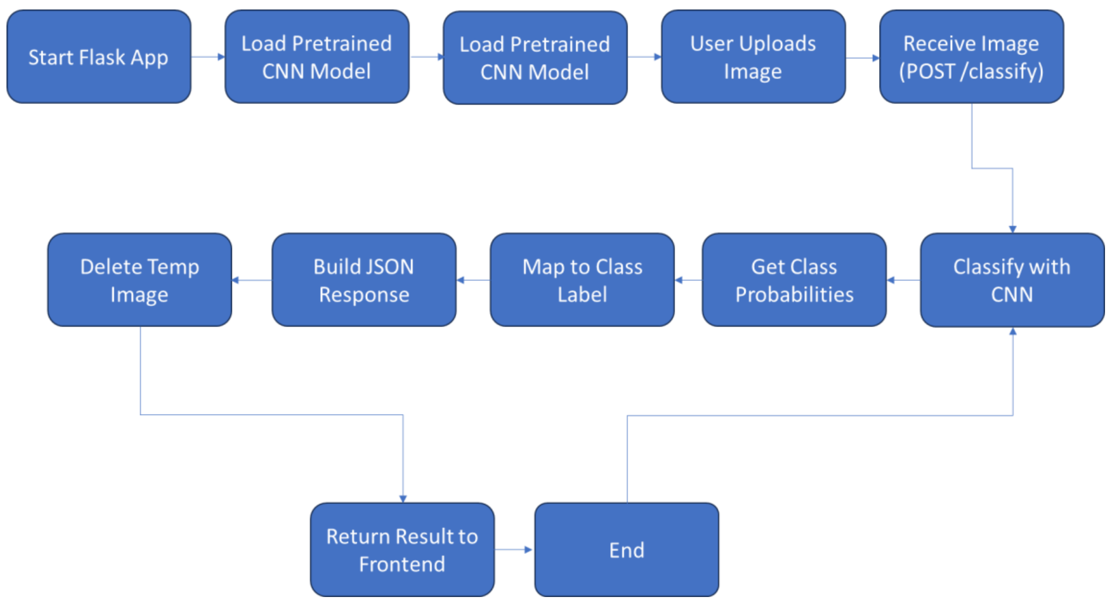


Figure 4: Server-side work flow

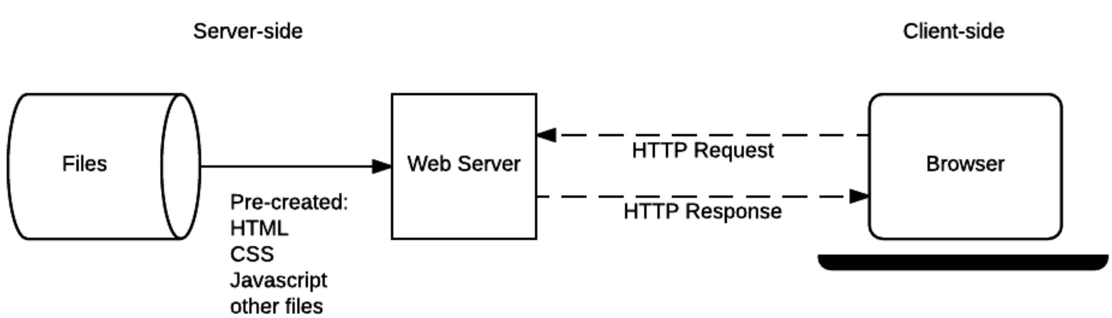


Figure 5: HTTP protocol work flow

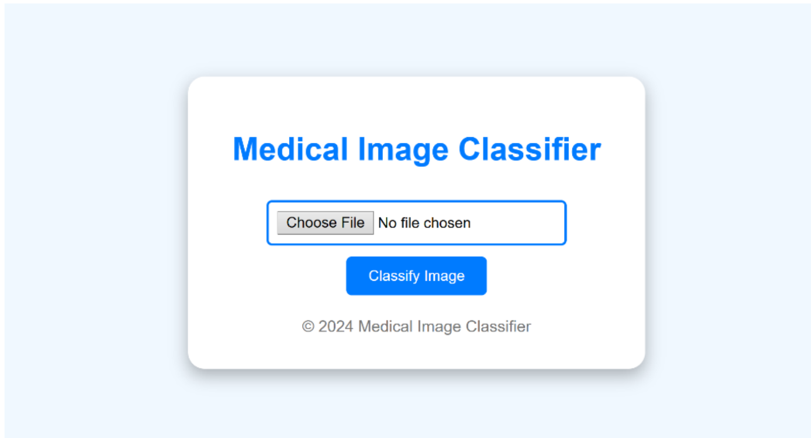


Figure 6: Client site web page to accept the files

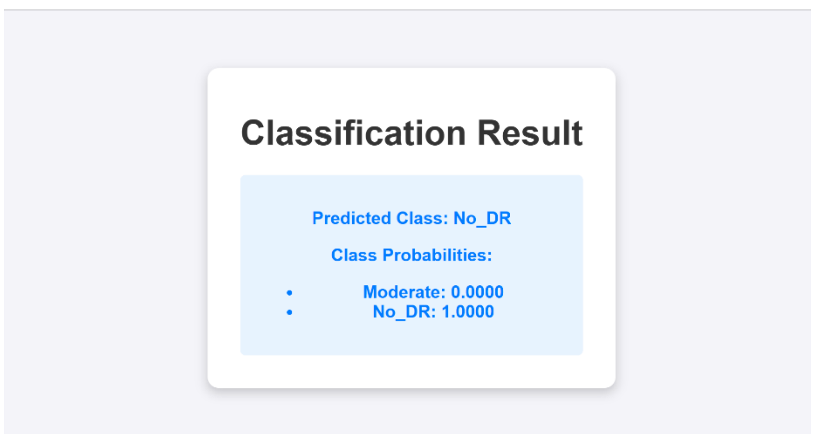


Figure 7: Client site web page show the classification results

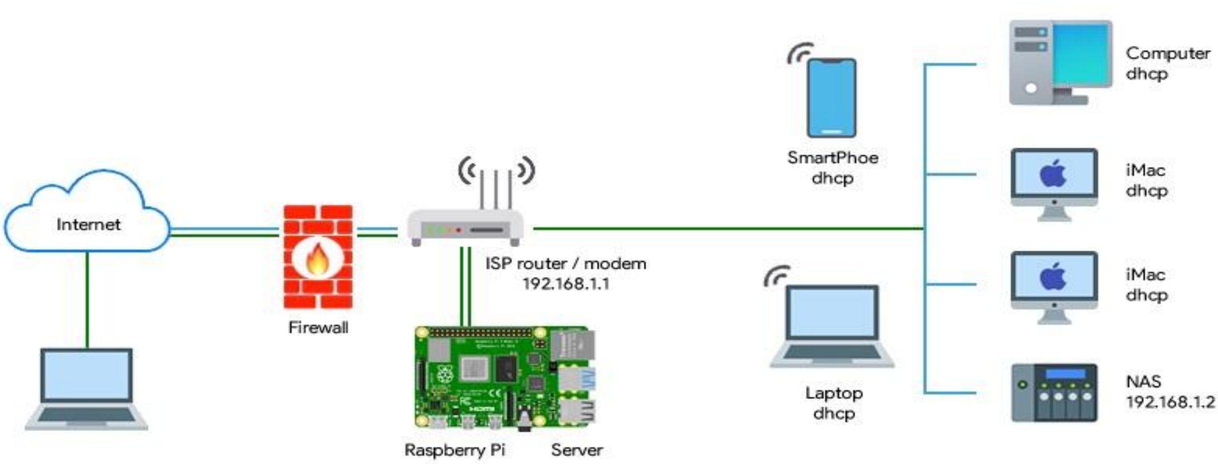
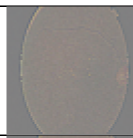
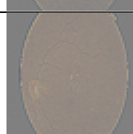
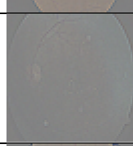
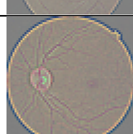
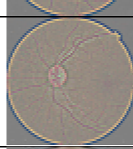


Figure 8: IOT system work flow

4.Results and Discussion

The dataset has images of patients from varying ethnicities, different age groups, camera sources with different lighting, and a variety of other factors through the fundus photographs that would alter pixel intensity values in the images and add unintended variation that would not apply to the classification levels, and variants which should be removed. For the purpose of color normalization of the high resolution and high memory, and then resizing the dataset to 32x32 pixels to incorporate some of the complex markings we would like to identify at, as well as meet the memory constraints of a NVIDIA K40c.

Table 2: Test accuracy for samples

Sample No.	Sample of Classification	Stage	Classification Probabilities	Accuracy	Final Classification
1		1	Moderate probability: 1.000 No Dr probability: 0.000	100%	Moderate
2		1	Moderate probability: 1.000 No Dr probability: 0.000	100%	Moderate
3		1	Moderate probability: 1.000 No Dr probability: 0.000	100%	Moderate
4		1	Moderate probability: 1.000 No Dr probability: 0.000	100%	Moderate
5		1	Moderate probability: 0.000 No Dr probability: 1.000	100%	No Dr
6		1	Moderate probability: 0.000 No Dr probability: 1.000	100%	No Dr
7		1	Moderate probability: 0.000 No Dr probability: 1.000	100%	No Dr
8		1	Moderate probability: 0.000 No Dr probability: 1.000	100%	No Dr

4.1 Model Testing Results

The dataset consisted of 1,998 retinal fundus images, equally divided between Moderate Diabetic Retinopathy (Moderate, 999 images) and No Diabetic Retinopathy (No_DR, 999 images). The data was split into 80% training (1,599 images) and 20% validation (399 images).

A Convolutional Neural Network (CNN) was trained on 32×32 pixel images for 10 epochs, using the Adam optimizer and binary cross-entropy loss. Training was performed on an NVIDIA GeForce GTX 1650 GPU, which significantly accelerated the process.

The model achieved the following performance metrics on the validation set:

- Validation Accuracy: 88.97%
- Precision: 97.28% (weighted average)
- Recall: 82.11% (weighted average)
- F1-score: 0.89 (weighted average)

The confusion matrix (Figure 9) shows that out of 181 Moderate images, 176 were correctly classified,

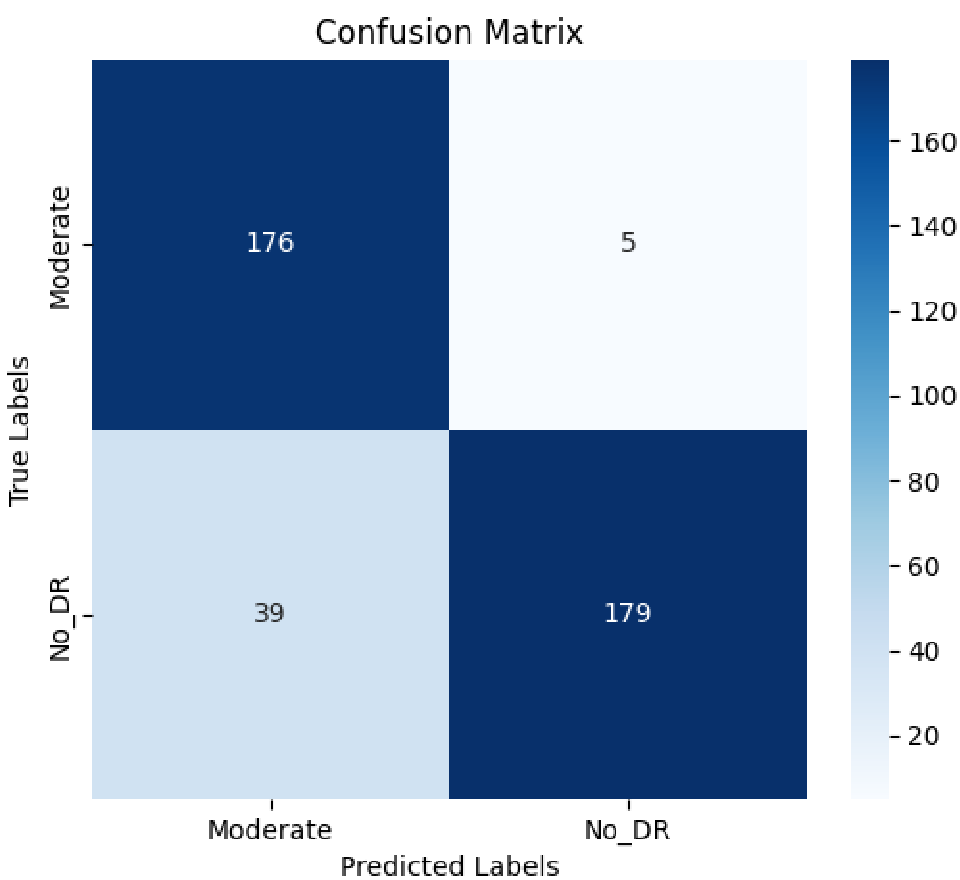


Figure 9: Confusion matrix showing the classification performance of the CNN on the validation dataset.

while 5 were misclassified as No_DR. For the No_DR class, 179 out of 218 images were correctly classified, while 39 were misclassified as Moderate.

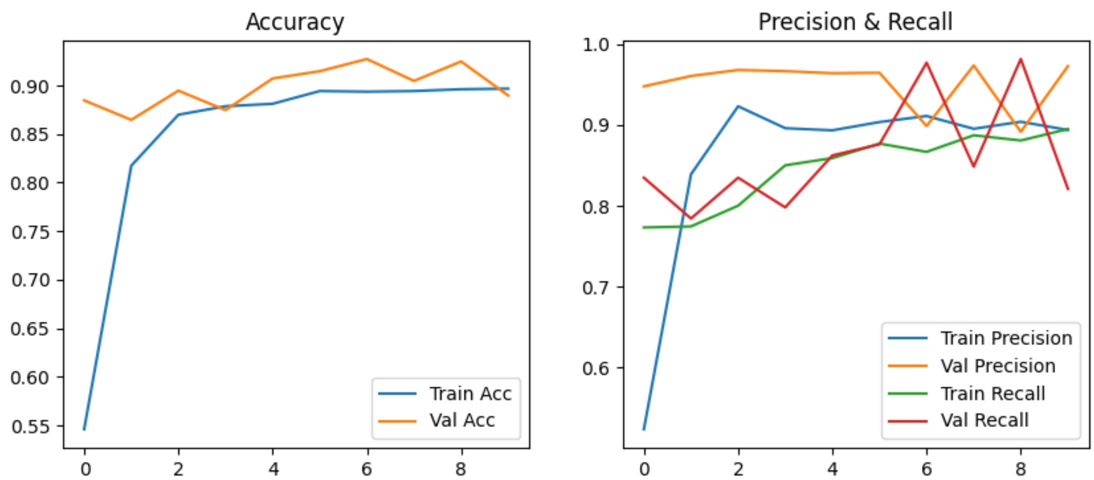


Figure 10: Training curves for accuracy, precision, and recall over 10 epochs, showing stable convergence with no signs of overfitting.

4.2 Classification Report

Class	Precision	Recall	F1-score	Support
Moderate	**0.82**	**0.97**	**0.89**	**181**
No_DR	**0.97**	**0.82**	**0.89**	**218**
Accuracy	**-**	**-**	**0.89**	**399**
Macro avg	**0.90**	**0.90**	**0.89**	**399**
Weighted avg	**0.90**	**0.89**	**0.89**	**399**

Table 3: Model testing Report

4.3 Performance of the proposed CNN

Study / Year	Dataset / Images	Method	Accuracy	Precision	Recall	F1-score	Notes / Comparison
Philip et al., 2007	14,406 images (screening programmed)	Automated “disease/no disease” grading	N/A	90.5% (sensitivity)	67.4% (specificity)	N/A	High sensitivity but lower specificity; your model has better class balance and higher precision for No_DR.
Mookiah et al., 2013	210 images	Early CAD systems for DR	81.3%	N/A	N/A	N/A	Older CAD systems had lower overall accuracy; your CNN achieves higher accuracy (~88.97%).
Benbassat & Polak, 2009	Various human grading studies	Reliability of screening methods	N/A	N/A	N/A	N/A	Highlights variability in human screening; your model provides consistent performance.
Proposed (2025)	1,998 images (999 Moderate, 999 No_DR)	CNN (32×32 images)	88.97%	0.9728 (weighted)	0.8211 (weighted)	0.89 (weighted)	Outperforms older CAD systems in accuracy and class-balanced precision/recall; demonstrates effective low-resolution classification.

5.Conclusion

Convolutional neural networks (CNNs) were employed to analyze retinal images to detect indicators of diabetic retinopathy. This type of network was proven capable of extracting important visual features without the need for human intervention or the use of predefined features. Reliable medical data was used, which helped achieve accurate and promising results. It was also indicated that the model could be developed in the future to be more specialized in classifying subtle disease conditions. This approach is expected to contribute to supporting medical staff by providing smart tools that aid in early and effective diagnosis, especially when combined with Internet of Things technologies. As data quality continues to improve and network architectures evolve, these models could become vital tools in smart healthcare applications.

Future Work:

To further improve the performance and generalizability of the proposed CNN model, future work could explore the use of deeper architectures, such as ResNet or EfficientNet, and advanced data augmentation techniques.

Additionally, incorporating transfer learning from pre-trained models and experimenting with hyperparameter optimization may yield better results.

Expanding the dataset to include more diverse and larger samples, as well as evaluating the model on external validation sets, would also strengthen the robustness and clinical applicability of the approach.

Resources

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