Bachelor of Science in Computer Science & Engineering

Building a Framework for Ensuring Balanced Nutrition by Prediction and Recognition of Fruits and Vegetables

by

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Abstract

Maintaining a balanced and healthy diet is a challenging task nowadays. In this thesis report, a framework has been proposed for ensuring balanced nutrition by prediction and recognition of fruits and vegetables. Most of the previous techniques have some limitations such as, some of them are good at recognition but some of them are not capable of ensuring balanced nutrition. Some of them are not able to suggest the right food for the right person. Another major contribution of this proposed framework is that three local storage have been created that had no existence before. All the data were scattered on the internet, but it has been organized here to make this proposed framework fully functional. This framework can identify 18 classes of fruits and vegetables with an accuracy of 97.8%. The recognition model is generated using CNN with the help of 23,224 train images and 7,892 validation images. Calorie requirement has been calculated using the Mifflin-St Jeor formula. Vitamin A, vitamin C, vitamin B6, sodium, potassium, calcium, protein daily requirement has been calculated using processed local storage. By identifying the 3 most lacking nutrients element the suggestion has been done using another processed local storage.

Keywords: CNN, BMR, RFPM,Pooling Layer, ReLU, Softmax.

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Chapter 1

Introduction

1.1 Introduction

Ensuring balanced nutrition is very crucial for common people.As a healthy human we need an average amount of vitamins and minerals.It is very necessary to maintain a balanced diet.Most of the people want to ensure their balanced diet each and every day but without a proper platform it has been very difficult.Due to this problem people are facing many health issues.Obesity is considered a global epidemic in adults and children [1].By investigation, it is found that, obesity is caused by excessive food consumption and lack of physical activity [2].A study shows that most of the female prefer a thin body and they are not satisfied with their body shape [3].Most of them wanted to beautify their appearance by limiting food intake and exercise [3].A study shows that, according to new generation of people, using innovative technology can be a way out of this balanced nutritional problem [4].Also, people are usually unaware of the fact about the quantity of nutrition intake.So, sometimes they cannot ensure it though there is availability of required fruits and vegetables. Therefore, there must be a way out of this problem.

In the past years, there have been rapid advancements in the field of artificial neural network.Many pioneer used this techonology to classify fruits and vegetables. Zaw Min Khaing developed a system using Convolutional Neural Network (CNN) to classify images of fruits and vegetables automatically [5].Guoxiang Zeng developed an image classification system for fruits and vegetables using Image Saliency and VGG model [6].He used convolutional neural network (CNN) to extract image feature [6].Parisa Pouladzadeh developed a system that can take an image, recognize this image using convolutional neural network and automatically calculates the calorie intake [7].

1.2 Framework/Design Overview

My focus is to remove the burdens for ensuring balanced nutrition.In previous years, the nutrition ensuring process was manual or semi-automatic.For example, a system was developed called Remote Food Photography Method (RFPM) where user has to upload two photographs before and after eating.The nutritionist then observe the amount of food intake and indicates about nutrition intake [8].In this proposed methodology, my main goal is to automate the full system as well as, telling the people which fruits or vegetables they should eat for accelerating balanced nutrition.The whole methodology is divided into the following basic steps:

- Recognizing an image of fruits and vegetables.
- Calculating the nutrition intake based on the recognized image.
- Indicating daily required nutrition intake.
- Suggesting fruits and vegetables based on nutrition lacking.

Block diagram of the proposed framework is given below:

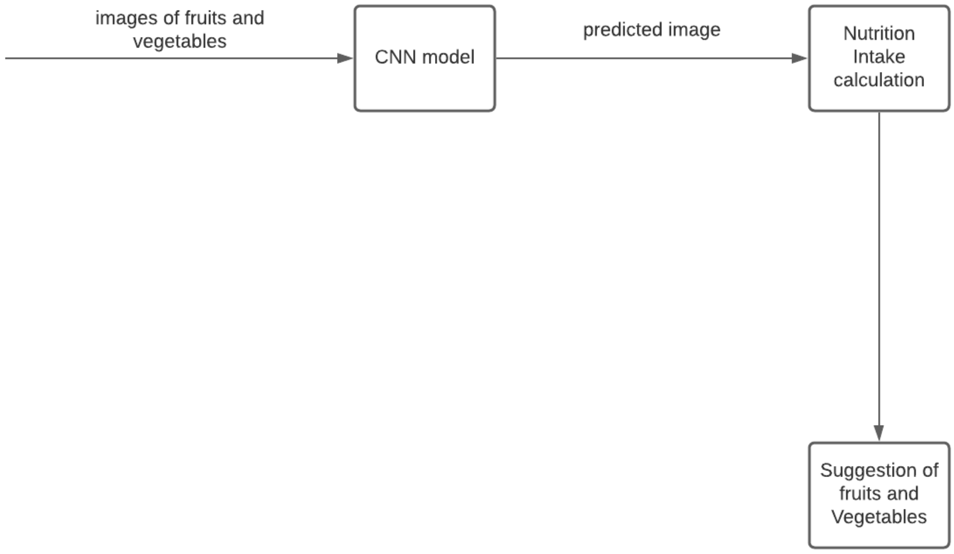


Figure 1.1: framework overview

1.3 Difficulties

There are some difficulties to implement this framework.Difficulties have been tried to overcome at the best possible way.

- For recognition purpose, the main difficulties are finding proper datasets for fruits and vegetables and computational cost for training the model.The crispier the data, the more accurate the recognition can be.Often the datasets are not well organized and there is defect in the images.On the other hand, the more the data, the more computational cost it requires.To, train a recognition model like CNN it requires many hours to complete the training.So, after changing some variables or tuning some parameters it becomes so hard to train the model again and again to get the most optimum result.
- During nutrition intake calculation we need to know the main nutrients of that recognized fruits or vegetables as well as the daily requirement of those nutrients for a particular user.But unfortunately, there is no organized data

or dataset for this purpose.All data and information is scattered in the vast website.Collection and organization of this data was made to make these tasks possible.

- Same situation implies for the suggestion part.To suggest or predict the required fruits or vegetables we need a organized database that is not available.So, this data has been organized from website and gathered together to make prediction easy.

1.4 Applications

The scale of application of any framework defines the quality of the framework.The application scale of this proposed methodology is vast.The applications are given below:

- This framework focuses on people of every age from 6 months to 51+ years.
- This framework recognizes 18 types of fruits and vegetables with accuracy of 97.8%.
- It then calculates BMR and nutrition intake for every age of male and female.
- Finally, it can suggest which fruits or vegetables are to be focused to ensure balanced nutrition by calculating nutrition lacking.

1.5 Motivation

There is a worldwide requirement of ensuring balanced nutrition.As nutrition is the key to live a healthy life.Eating nutrient-rich food helps an individual with necessary energy and helps acquiring a good state of mind [9].There is a daily requirement of nutrition for every human.One way to calculate nutrition intake is by identifying the foods (fruits or vegetables) people consume [10].People also should be careful about what they are consuming.Because, unhealthy food consumption may increase the possibility of obesity [11].To prevent obesity and other health issues that are caused by unhealthy food intake dietary monitoring systems are being developed worldwide [12].The public's desire for a stronger dietary support mechanism as a response to obesity has prompted researchers to focus on food recognition [13].Food recognition is an emerging technology that assists people in estimating food calories while also analyzing their eating habits [14].Food image recognition has a great impact on ensuring daily balanced diet [15].Traditional food logs using paper journals and mobile apps are the most well-known methods for long-term food consumption monitoring, but these have low adherence due to burdensome procedures for users that can only be tested during short-term tracking [16].Since manual food journaling has limited functions and capabilities, the production of automated food logging applications based on image recognition has exploded [17].As the technology trend dictates, food recognition software that calculates the nutritional value of food based on images of the food has made a significant positive impact in assisting people in managing their health and eating habits.Monitoring and assessing food consumption is critical in the treatment of obesity and other health problems [18].

1.6 Contribution of the thesis

The aim of a thesis or research project is to achieve a particular set of objectives, such as defining a new approach or improving an existing one.The main goal of this proposed methodology is to ensure balanced nutrition by recognition of fruits and vegetables and predicting correct fruits or vegetables to consume for a particular user according to their age and gender.The main contribution of this framework is given below:

- This framework will recognize 18 types of fruits and vegetables.
- Nutrition intake calculation by making an organized local storage of nutritional facts of fruits and vegetables that is shown in figure 3.8.
- During nutrition intake indication this framework uses another organized local storage that helps to understand the total nutrition requirement for any person using figure 3.9.

- This framework suggests the most needed fruits and vegetables by using another local storage in figure 3.10.

In short, it can be said that, this framework is a 3 in 1 framework.It is the combination of

- Recognition
- Nutrition Indication
- Suggests fruits and vegetables

This framework presents 3 different features in one platform to get the best result for ensuring balanced diet.

1.7 Thesis Organization

The rest of this thesis report is organized as follows:

- Chapter 2 gives a brief summary of the work done related to "Ensuring Balanced Nutrition by recognizing and predicting fruits and vegetables".
- Chapter 3 is about methodology of this proposed framework.In this chapter the total work procedure is discussed elaborately.
- Result and performance evaluation as well as framework evaluation is shown in Chapter 4.
- Chapter 5 contains overall summary of this thesis report as well as further plan about the proposed framework.

1.8 Conclusion

In this chapter, an overview of proposed framework is provided. Along with the difficulties, the summary of the Ensuring Balanced Nutrition by recognizing and predicting fruits and vegetables is described in this chapter. The motivation behind this work and contributions are also stated here. In the next chapter, background and present state of the problem will be provided.

Chapter 2

Literature Review

2.1 Introduction

There are total 3 parts of the framework.Firstly, image recognition is done by deep neural network.CNN (Convolution Neural Network) has been used to predict image correctly.Secondly, after identifying the fruits or vegetables, the nutrition amount present in that particular fruits or vegetables are fetched from a csv(comma separated value) file.It then can show a user how much vitamins and minerals have been used by that user.Thirdly, after calculating daily shortage of vitamin and minerals, a prediction system is developed, that can suggest which fruits and vegetables should be intake most based on daily intake for a particular user.It is hard to find a system that meets the above mentioned 3 parts combined.Many related works are found only on image recognition or only on finding nutrition from fruits and vegetables or only on predicting vegetables and fruits.But it is hard to find a framework that combines the three of them.

2.2 Related Literature Review

In this section we are describing some of the common technologies that has been developed in recent years as well as their drawbacks.Some related frameworks are discussed below:

2.2.1 Platemate

Platemate is a framework that allows the system to take some photographs of a plate with different foods cooked or uncooked [19].Then it uses "Amazon Mechanical Turk" to calculate the nutrition amount for the plate of food.Platemate uses

crowdsourcing to analysis nutritional facts by using untrained workers.Platemate returns the nutritional facts after spending some time or after a fixed duration.Platemate focuses on overcoming the traditional self-reporting system where a user has to report to a nutrition specialist regularly to ensure nutritional balance.Platemate is inspired by *Remote Food Photography Method*(RFPM) [8].In this RFPM method, user has to upload two photographs.One is before starting eating the food and another is after finishing eating.The two photographs are then sent to a server for observation.Nutrition specialist observe the food intake amount and reports about the nutrition intake about that user.
A recent study has found out that, this naive crowdsourcing method is not enough for ensuring nutritional balance of a user.Also, the limitation of RFPM method is, it is mostly manual. No automation is implemented here and it is more costly as it requires special personnel about nutrition.

2.2.2 NutriNet

It is a image recognition architecture that uses deep convolution neural network [20]. It can detect foods as well as drinks. This architecture can detect images with an accuracy of 86.72%. The dataset contains 225,953 images of 520 different classes. Images were of 512*512 pixels.
This architecture has only been used for food and drinks recognition.

2.2.3 Calorie measurement using deep learning neural network

This proposed system allows user to take pictures with their smartphone and automatically recognizes this image using deep learning neural network [7].They used convolutional neural network to train 10,000 images and gained 99% of accuracy for a single food recognition.
This system is only used for calorie intake calculation by identifying foods. Also, the datasets are limited in number.

2.2.4 NutriTrack

This is an android application that focuses on raising consciousness among the people those are not nutrition expert [11]. This system allows user to take photo of the food intake and tells it's nutritional contents.By calculating daily calorie intake using Mifflin-St Jeor method this system also indicates the calorie intake for the user by recognizing the fruits and vegetables.

The main problem of NutriTrack is, it is built on two APIs and the APIs are paid.NutriTrack uses **Clarifai** API to recgonize fruits and vegetables and **Nutritionix** API to estimate the nutritional values of the photographs.It cannot estimate about other nutritional elements like vitamin A intake,vitamin C intake, sodium, magnesium, potassium intake etc. Also, it can't provide necessary information on which foods and vegetables to consume for a particular user to ensure one's balanced nutrition intake.

2.2.5 Snap, Eat, Repeat

Another research, "Snap, eat, repEat," uses a dataset of 500 food categories and approximately 150,000 photos of cooked meals to develop a framework for food identification in the sense of dietary evaluation and logging [17].This system performs food recognition in two cases using photos taken with their phone.The first scenario is called "Food in context".In this scenario they exploit GPS information to locate the restaurant's location narrowing the food items.The second scenario is called "Food in the wild".In this scenario they try to recognize cooked foods by images taken with mobile phone cameras.

2.3 Conclusion

Some related works have been discussed in the above subsection. All of them had some limitations.Some of them had low number of datasets. While some of them were not focused to calculate vitamins and minerals for the users. All of the mentioned limitations have been tried to overcome in this proposed framework. The methodoloy is discussed in the next chapter.

Chapter 3

Methodology

3.1 Introduction

This methodology stands on three basic parts.Image recognition, nutrition intake calculation and suggestion of fruits and vegetables for ensuring balanced intake of nutrition. For better accuracy and better result every step has been considered carefully.For recognition part, deep convolution neural network has been used.It is one of the most popular technology for image recognition.To calculate daily calorie calculation, Mifflin-St Jeor formula has been used as it is the most accurate formula to calculate BMR (Base Metabolic Rate).Other nutrients elements has been collected from Google according to age and gender from authentic source.To suggest the right fruits and vegetables another database has been used to fetch the right data for the right user according to age and gender of that particular user.

3.2 Diagram/Overview of Framework

The total methodology includes the main features like recognition of fruits, calculating nutrition intake and suggesting proper fruits and vegetables.Graphical interface or graphical representation of the methodology helps to visualize the process beautifully. The total steps overview and diagram is discussed below:

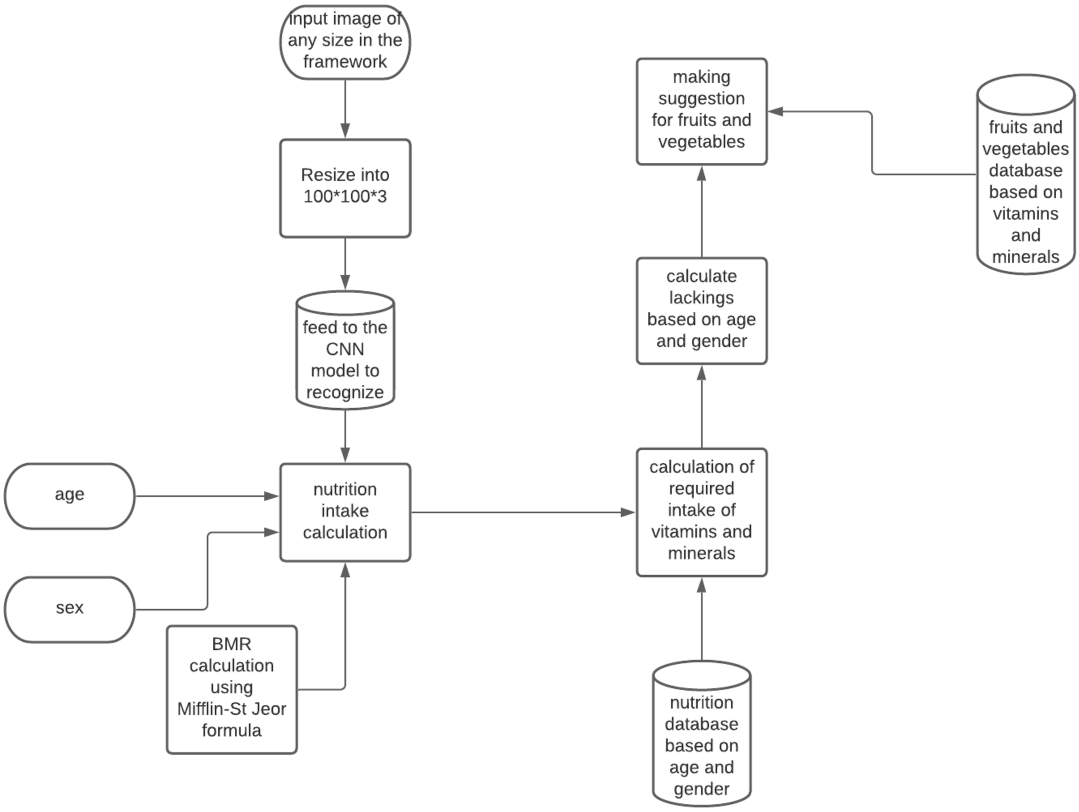


Figure 3.1: Diagram of proposed methodology

in 3.1 the steps required for implementing proposed methodology is shown.

- At first, any image of fruits or vegetables are fed into the system.
- Then, the image is resized as, it will be used to predict the image in CNN model.
- A CNN model is used to recognize the image.
- After recognizing the image, total nutrition intake is calculated using the user's age, gender and nutrition database. Nutrition database is created with the help of trusted website.
- Then, according to the daily requirement of that user, a statistics is created indicating over consumption or lack of consumption.The lacking is calculated based on age and gender.
- Finally, a suggestion is created based on the lacking calculation. It calculates, which element of vitamins and minerals are taken the least.Then,

it tells which fruits and vegetables are to take so that the lacking can be overcome.

3.3 Detailed Explanation

Our proposed methodology for implementing this framework is divided into three basic parts.So, detailed explanation of this framework is discussed into three main subsections.The subsections are discussed in details below:

The most challenging part of this framework is the recognition part. Because, to identify an image correctly, the computer must learn some complex mathematical formulae.In previous years, images were classified using traditional classification approach such as, classification algorithm. But they are inefficient to recognize an image in case of large number of data.
Deep neural network plays a better role in such a case.The larger the data set, the more wide range of images the system can detect.For large number of data sets, deep neural network approach shows better accuracy compared to traditional SVM image classification method [21].Among different deep learning methods CNN is remarkably better at image recognition as Alex Krizhevsky used deep convolutional neural network to sort the 1.2 million high-resolution images submitted to the ImageNet LSVRC-2010 contest into 1000 distinct groups [22].So, CNN has been chosen to use for the recognition part of the proposed framework.

3.3.1 Flow chart of fruits and vegetable recognition

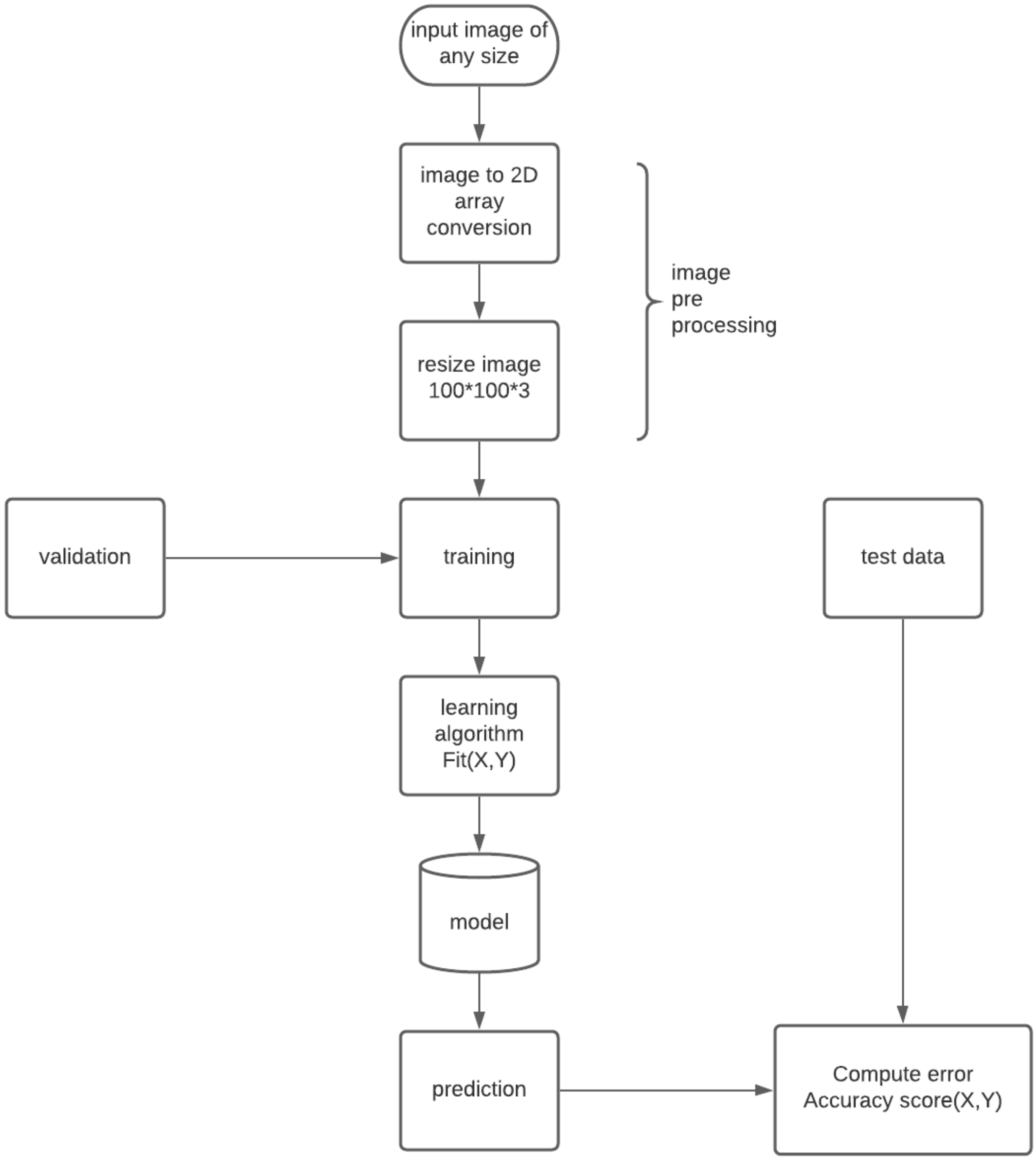


Figure 3.2: Diagram for image recognition process

In figure 3.2 it is shown that first image is preprocessed before fitting into the algorithm.Then a model is created for predicting the image.

3.3.2 Human vs Machine Vision

It is completely different how a machine sees the world compared to how we see the world. We see the world by seeing the color, size and many more attributes.But the computer or any other machine sees the world only by number.It sees the world by pixels.Each pixel corresponds to a number between 0 to 255.A picture is a combination of many more pixels.So, when a machine sees a picture, it actually looks at a 2 dimensional matrix created by many more pixels. The image given below can help to visualize this scenario.

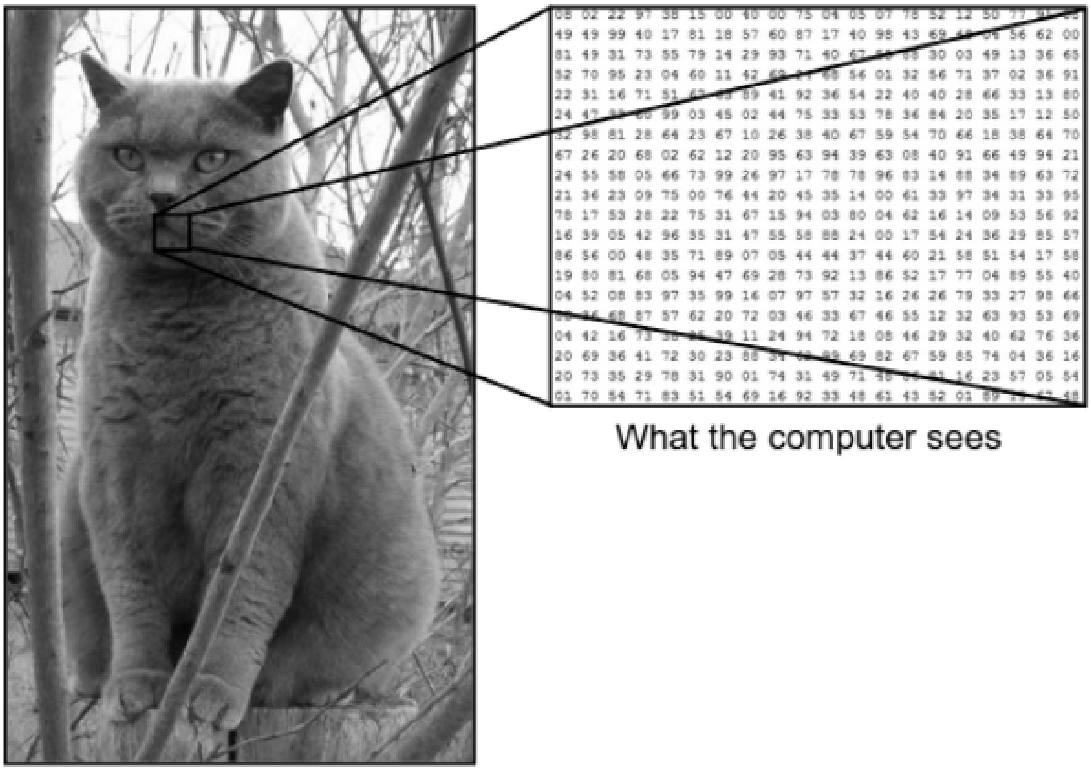


Figure 3.3: Human vs computer vision

In figure 3.3 it is shown that, a single portion of the image contains many more pixels.So, a single portion of the cat image is a huge 2 dimensional matrix.That means, for image detection and recognition first of all, we need to convert an image to a 2D array, so that computer understands the image well.

3.3.3 Image preprocessing

- Before fitting the image into training model the image must be preprocessed.The image should be in a fixed format.So that it can be fit into the training model.To make the image reach to that desired state, the image first converted into a 2D array.All the values in that 2D array are between

0 and 255.There are many available tools to do this.**opencv2** is a popular python package to accomplish this.This package has been used in this methodology.

- Then, the image is normalized to avoid large computational time.By complex calculation performed on the pixel values the values can be large and it may take more space and computational time to accomplish the training process.So, the values are normalized to small numbers between 0 to 1.Each pixel value is divided by 255, so that each pixel value converts into between 0 to 1.The formulae can be written as:

$$pixelValue = pixelValue/255.0 \tag{3.1}$$

- Image is then resized to get a fixed size of length and width.If different images have different width and length size, then there is different number of pixels for a same image.For example, if an image of cat is 50*50 pixel, then it has total of 250 pixels. If the same image is of 100*100 pixel, then the image has total 10000 pixels.It is hard to train a model of different sized 2D array of same cat's picture.It becomes difficult to find a pattern for the model.So, it is necessary to resize the images to a fixed width and length.

- The next step is to fix the color mood of the image.Color mood or color channel fixing is necessary because it impacts the pixel shape and size.For example, in grayscale color mood a 50*50 image has total 250 pixels.But in rgb color mood there will be total of $50*50*3 = 7500$ pixels.So, there will be problem to find a pattern in this case also as there are different number of pixels for a same picture.So, it is necessary to fix the color channel.There are 3 types of color channel:**grayscale, rgb and rgba**.For better recognition accuracy it is better to use rgb or rgba color mood.In this methodology rgb color mood has been used.

3.3.4 CNN model architecture

Convolutional Neural Networks are a form of Deep Neural Network used primarily in visual imagery in Deep Learning.
The key feature extraction process takes place in the first section, which consists of the Convolutional and Pooling layers. The Fully Connected and Dense layers, which serve as the classifier in the second section, perform several non-linear transformations on the extracted features.
In other words, CNN is the combination of convolutional layers and ANN layers.Feature extraction process is done in convolutional and pooling layers.As human we see base feature of cat as it's nose, eye etc.But computer counts base feature as curvature, line, boundaries etc. from the 2D matrix.It is called base feature extraction.

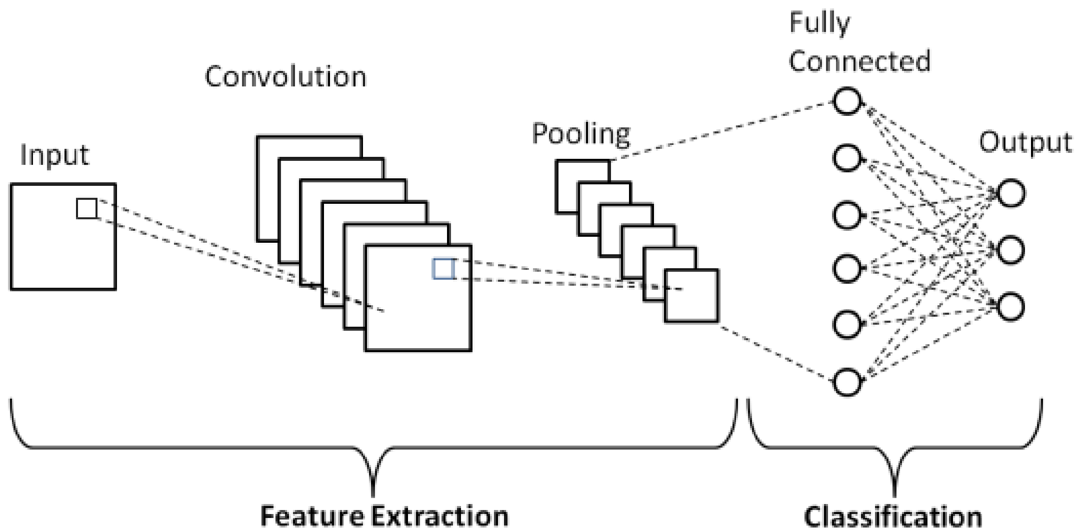


Figure 3.4: Basic CNN architecture

Convolutional Neural Network model consists of different types of layers:

- Input Layer
- Convolutional Layer
- Pooling Layer
- Fully Connected Layer

- Output Layer
- Activation Function

Each of the layers are discussed below in brief:

3.3.4.1 Input Layer

We can deduce from the name that this is the layer that will feed the input image to the CNN model. We can reshape the image to different sizes depending on our needs, such as (28,28,3).In our implementation we have used input size of (100,100,3).Here, 100 is the number of pixel in length and widht of the picture and 3 is for color channel(RGB color mode).

3.3.4.2 Convolutional Layer

It is the most important model of CNN architecture as it extracts the base feature from an image such as sharp edges or curvatures.It consists of a filter (also known as kernel), which is of fixed size.The feature extraction process happens between the input layer and the kernel or filter.This is also known as feature extractor layer.In our implemented methodology, 4 convolutional layers have been used.In first convolutional layer 16 neurons have been used.Similarly, in 2nd, 3rd and 4th convolutional layers consist of 32, 64 and 128 neurons respectively.Our kernel shape is (3,3) that is used in base feature extraction.

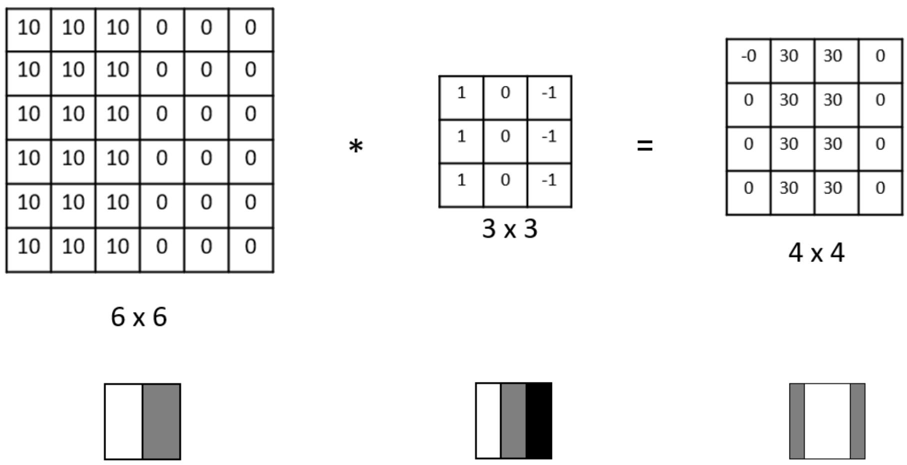


Figure 3.5: Feature extraction using (3,3) kernel

In figure 3.5 the leftmost matrix is the main input image that is being filtered through the (3,3) kernel.The dot product of the first (3,3) chunk of the (6,6) matrix and the (3,3) kernel will be transformed into one single value.Thus the whole (6,6) matrix will be converted into (4,4) matrix.

3.3.4.3 Pooling Layer

After extracting feature in convolutional layer, we use pooling layer.As it decreases the spatial volume of the images, this layer is also called downsampling layer.In figure 3.5 we got an output of (4,4) matrix.But to increase efficiency and to avoid unnecessary calculation we can divide the (4,4) matrix into (2,2) by taking the most significant values that matters to the model.This process is called pooling.So, this computational layer is called pooling layer.A sample visualization is given below:

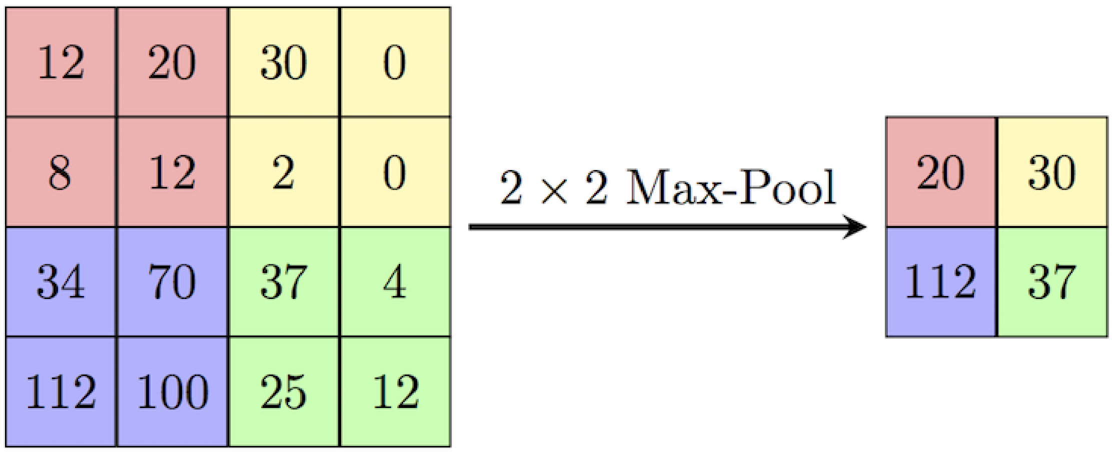


Figure 3.6: Pooling layer with stride of 2

In figure 3.6 it is shown that, the (4,4) matrix is divided into 4 chunks.From 4 chunks we get 4 most significant values that creates the output (2,2) matrix.

3.3.4.4 Fully Connected Layer

The Fully Connected Layer (FC) is added just before the CNN model's final classification production. Until classifying, these layers are used to flatten the data. Several biases, weights, and neurons are involved. Until classification, attaching a completely connected layer produces an N-dimensional vector, where

N is the number of classes from which the model must select one.The loss functions is calculated here.

3.3.4.5 Output Layer

Output layer contains the labels of the samples that is encoded using one-hot encoding method.The number of neurons in the output layer are equal to the classes that the system will predict.In our system, 18 neurons have been used as we have detected total 18 types of fruits and vegetables.In my methodology, softmax activation function has been used in the output layer.This function gives a number between 0 to 1 for each node of output layer.It detects the maximum number of the corresponding node and detects as the final output.So, this activation function is also called probability distribution function.

3.3.4.6 Activation Function

Any Convolutional Neural Network model is built around these Activation Functions. These functions are used to calculate a neural network's performance. In a nutshell, it decides whether or not a specific neuron should be triggered ("fired"). Non-linear functions are normally applied to the input signals in this case. The next layer of neurons receives this transformed output as an input. The Sigmoid, ReLU, Leaky ReLU, TanH, and Softmax are some of the activation functions.In each layer we have used ReLU activation function except the output layer where softmax functions has been used.If the input is positive, the ReLU function will output that data directly otherwise it will output zero.

3.3.4.7 Model Summary

In summary, for creating the CNN model I have considered the following parameters:

- input image size is (100,100,3)
- 16,32,64 and 128 neurons in 1st, 2nd, 3rd and 4th convolutional layers.
- (3,3) kernel size has been used.
- in pooling layer stride size 2 has been used.

- a dense layer containing 512 neurons has been used just before output layer with ReLU activation function.
- final output layer contains 18 neurons which is activated with softmax activation function.

So, total model summary considering the above mentioned parameters with input and output shape looks like this:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 98, 98, 16)        448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 49, 49, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 47, 47, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 23, 23, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 21, 21, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 10, 10, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 128)         73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 512)               1049088
_________________________________________________________________
dense_1 (Dense)              (None, 18)                9234
=================================================================
Total params: 1,155,762
Trainable params: 1,155,762
Non-trainable params: 0
```

Figure 3.7: CNN model summary

3.3.5 Training the model

For training the above mentioned CNN model in section 3.3.4 with the training data the model must be compiled first with some parameters.The parameters or arguments are briefly discussed below:

- For computing loss function "categoricalcrossentropy" has been used.As there is more than 2 label classes, it is better use this loss function in this scenario.

- There are many optimizer available.Among them, RMSprop optimizer has been used here as it implements RMSprop algorithm.
- accuracy metrics has been used to determine the accuracy of the model.

Using these parameters the CNN model is compiled and then the dataset is fit into the model to train. 10 epochs was enough to reach the validation accuracy of 97.88%.After training the model some curves like 'training and validation accuracy' or 'training and validation loss' can be generated.

3.3.6 Nutrition intake calculation

After predicting the image the system should calculate nutrition intake for that particular user based on the predicted image.To calculate nutrition intake first we should calculate daily required calories for each user.To calculate daily required calories, we need to calculate Basal Metabolic Rate(BMR).

Endothermic animals' basal metabolic rate is the rate of energy consumption per unit time when they are at rest. Energy units per unit time range from watt to ml O2/min, or joule per hour per kg body mass J/. A specific set of requirements must be followed in order for proper measurement to take place.There are two popular methods to calculate BMR. But the formulae of Mifflin-St Jeor gives better accuracy.The formula is given below:
For male the equation is,

$$bmr = 10 * weight(inkg) + 6.25 * height(incm) - 5 * age - 161 \tag{3.2}$$

And for female the equation is,

$$bmr = 10 * weight(inkg) + 6.25 * height(incm) - 5 * age + 5 \tag{3.3}$$

In order to calculate required calorie intake using BMR we need to consider 5 types of working activity.By using scores of corresponding activity we can calculate calorie intake for a particular person.The 5 types of daily activities are-

- little or no exercise
- lightly active (light exercise/sports 1-3 days/week)
- moderately active (moderate exercise/sports 3-5 days/week)
- very active (hard exercise/sports 6-7 days a week)
- extra active (very hard exercise/sports and physical job or 2x training)

in case of 'little or no exercise':

$$calorie = bmr * 1.2 \tag{3.4}$$

in case of 'lightly active (light exercise/sports 1-3 days/week)':

$$calorie = bmr * 1.375 \tag{3.5}$$

in case of 'moderately active (moderate exercise/sports 3-5 days/week)':

$$calorie = bmr * 1.55 \tag{3.6}$$

in case of 'very active (hard exercise/sports 6-7 days a week)':

$$calorie = bmr * 1.725 \tag{3.7}$$

in case of 'extra active (very hard exercise/sports and physical job or 2x training)':

$$calorie = bmr * 1.9 \tag{3.8}$$

After calculating daily calorie intake we need to calculate how many vitamins and minerals that person should consume more.To calculate this, we need some type of database holding the information of vitamins and minerals amount in the fruits and vegetables.These information were gathered from trusted nutrition related website and put together into a csv file.

name	calories	potassium_g	carbohydrate_g	vitamin_a_g	vitamin_c_g	calcium_g	vitamin_b6_g	magnesium_g	protein_g	sodium_g
apple	52	0.107	14	0.000192857142	0.0046	0.006	0	0.005	0.3	0.001
banana	89	0.358	23	0.000228571428	0.0087	0.005	0.0004	0.027	1.1	0.001
cauliflower	25	0.299	5	0	0.0482	0.022	0.0002	0.015	1.9	0.03
corn	107.92	0	38.5	0	0	0.67	0.0007	0.345	3.4	0
date	282	0.656	75	0	0	0.039	0.0002	0.043	2.5	0.002
eggplant	25	0.229	6	0	0.0022	0.009	0.0001	0.014	1	0.002
ginger	80	0.415	18	0	0	0.016	0.0002	0.043	0	0.013
guava	68	0.417	14	0.002228571429	0.2283	0.018	0.0001	0.022	2.6	0.002
lemon	29	0.138	9	0	0.053	0.026	0.0001	0.008	1.1	0.002
lychee	66	0.171	17	0	0.0715	0.005	0	0.01	0.8	0.001
mango	60	0.168	15	0.003864285714	0.0364	0.011	0.0001	0.01	0.8	0.001
onion	40	0.146	9	0.000007142857	0.0074	0.023	0.0001	0.01	1.1	0.004
orange	47	0.181	12	0.000803571428	0.0532	0.04	0.0001	0.01	0.9	0
papaya	43.27	0.14	6.9	0.001809535714	0.06	0.01622	0.00004	0.021	0.4	0.0073
pineapple	50	0.109	13	0.000207142857	0.0478	0.013	0.0001	0.012	0.5	0.001
pomegranate	82.97	0.23617	53	0	0.01021	0.01	0.000075	0.012	3	0.00301
potato	87	0.421	17	0	0.0197	0.012	0.0003	0.023	2	0.006
tomato	18	0.237	3.9	0.000523821428	0.0293	0.01	0.00015	0.011	0.9	0.005
watermelon	30	0.112	8	0.002032142857	0.0081	0.007	0	0.01	0.6	0.001

Figure 3.8: nutrition list for vegetables and fruits

In figure 3.8 the above mentioned vegetables and fruits in 4.2 are shown.Each fruit and vegetable is considered 100gm in quantity.The vitamins and minerals considered in this case are:

- calories
- potassium in gram
- carbohydrate in gram
- vitamin a in gram
- vitamin c in gram
- calcium in gram
- vitamin b6 in gram
- magnesium in gram
- protein in gram
- sodium in gram

Each vitamin and mineral is calculated in 100 gm of fruits and vegetables in figure 3.8 Now, we need the daily intake requirement amount for potassium, carbohydrate, vitamin a, vitamin c, calcium, vitamin b6, magnesium, protein and sodium.Because, we can only calculate daily calorie intake by Mifflin-St Jeor formula.So, I have created a local database for the daily requirements of these vitamins and minerals.With the help of many nutrition based trusted website, the database is created.A portion of the database is given below:

age	sex	vitamin_a_gm	vitamin_c_gm	vitamin_b6_gm	sodium_g	potassium_g	magnesium_g	calcium_g	protein_g
0.5	male	0.0005	0.05	0.0003	0	0.4	0.03	0.2	0
0.5	female	0.0005	0.05	0.0003	0	0.4	0.03	0.2	0
1	male	0.0003	0.015	0.0005	1	0.86	0.075	0.26	13
1	female	0.0003	0.015	0.0005	1	0.86	0.075	0.26	13
2	male	0.0003	0.015	0.0005	1	2	0.08	0.7	13
2	female	0.0003	0.015	0.0005	1	2	0.08	0.7	13
3	male	0.0003	0.015	0.0005	1	2	0.08	0.7	13
3	female	0.0003	0.015	0.0005	1	2	0.08	0.7	13
4	male	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
4	female	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
5	male	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
5	female	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
6	male	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
6	female	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
7	male	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
7	female	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
8	male	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
8	female	0.0004	0.025	0.0006	1.2	2.3	0.13	1	19
9	male	0.0006	0.045	0.001	1.2	2.5	0.24	1.3	34
9	female	0.0006	0.045	0.001	1.2	2.3	0.24	1.3	34
10	male	0.0006	0.045	0.001	1.5	2.5	0.24	1.3	34
10	female	0.0006	0.045	0.001	1.5	2.3	0.24	1.3	34
11	male	0.0006	0.045	0.001	1.5	2.5	0.24	1.3	34

Figure 3.9: Daily required vitamin and minerals intake according to age and sex

In figure 3.9 some portion is shown.It is estimated using age and gender.Age starts from 0.5 years to 51 years.The database is created considering each age between 0.5 years to 51 years depending on gender.This database helps to visualize and calculate daily vitamins and minerals intake for a particular user aged between 0.5 to 51 years both male and female.

So, the total procedure looks like this - after recognizing the image of fruits and vegetables by the CNN architecture mentioned in 3.3.4 we have to input the quantity of consumed fruits or vegetables.Then, we can calculate total consumed vitamins and minerals using figure 3.8.After subtracting the consumed amount from daily required intake using figure 3.9 the consumption percentage can be calculated.This consumption percentage tells us, which vitamins and minerals are consumed the least in quantity.The formulae can be written like this:

$$indicator = DailyRequiredIntake - DailyTotalIntake \tag{3.9}$$

Here,

- *indicator* indicates the total lack of vitamins and minerals or how much excessive nutrition has been taken.
- *DailyRequiredIntake* will be used from figure 3.9.
- *DailyTotalIntake* will be used from figure 3.8

3.3.7 Fruits and Vegetables Suggestion

From section 3.3.6 we can use this system as an indicator so that it can detect which vitamins and minerals are to take much or which nutrients are consumed less than the requirement.In my system, I have calculated the percentage of lacking for each vitamin and mineral like this:

$$percentage = indicator * 100/DailyRequiredIntake \tag{3.10}$$

The variables *indicator* and *DailyRequiredIntake* are from equation 3.9.After calculating percentage of each nutrient the top least amount of nutrition intake is considered for further approach.For example, if for a particular person sodium, magnesium, vitamin b6 and vitamin a daily intake lacking is 20%, 40%, 10% and 50% respectively then, sodium, magnesium and vitamin a is considered to be the most needed nutrients to intake for that particular user.Then it becomes easy to suggest for that user which nutrients should be suggested for him/her.Also, we have to suggest such fruits and vegetables those contain the lacking nutrient most.For this example, we have to suggest such fruits and vegetables that contains sodium, magnesium and vitamin a most.To accomplish that, we need a database that contains name of fruits of vegetables based on nutrients.A database has been made using trusted websites.A snapshot of the database is given below:

name of nutrient	fruits and vegetables
calories	banana, avocado,coconut, mango
potassium	potatos, sweet potato, pea, cucumber, pumpkin
vitamin a	sweet potato, carrot, mango, papaya, pumpkin
vitamin c	orange, lemon, guava, strawberries
calcium	Soyabean, broccoli, fig
vitamin b6	peanuts, soyabean, banana
magnesium	figs, avocado, banana, raspberries

Figure 3.10: fruits suggestions based on particular nutrient

From figure 3.10 it is shown that, if a particular nutrient such as magnesium is taken the least, then figs, avocado, banana, raspberries have to be suggested.Thus, by identifying the 3 least nutrient it is possible to select corresponding 3 rows from fig 3.10 and it is possible to let the user know, which fruits and vegetables are to intake most.

3.4 Conclusion

In this chapter, the proposed methodology for building a framework for ensuring balanced nutrition by image recognition using deep learning has been discussed in detail.It is shown that, how a single picture as well as some user information can be implemented to ensure balanced nutrition for a particular person or user.The next chapter is about results and discussions about this proposed methodology.

Chapter 4

Results and Discussions

4.1 Introduction

In the previous chapter, the methodology for building a framework for ensuring balanced nutrition using deep learning technique has been discussed in details.

This framework is implemented using keras and tensorflow backend.The full calculation is done using Google CoLab.Google CoLab provides 12 GB of RAM and 107 GB of virtual storage.I have tried to bring the best possible results by following various techniques.

4.2 Dataset Description

For acquiring better prediction accuracy a good quality dataset is necessary.I have tried to consider the best dataset available for my system.The whole dataset is divided into 2 categories:

- train dataset
- validation dataset

For training purpose for the system 23,224 images have been used in the training folder.The CNN model tries to find some patterns by using the images in training folder.The 23,224 images belong to total 18 classes.Because, we have tried to identify total 18 types of vegetables and fruits.Training data is used to find the model accuracy.In this proposed methodology model accuracy was found 99.91%.Similarly, in validation folder 7,892 images have been used belonging to 18 classes.This is used to determine how good the prediction of the model is.It is also called validation accuracy.The images of validation dataset is different from the training dataset.During training the model, images of validation dataset are used to determine if the prediction is right or wrong.

In both training and validation datasets the image shape is (100,100,3).100 stands for the length and width of the image and 3 stands for RGB channel. For creating a better dataset, A 20-second movie was filmed after fruits and vegetables were planted in the shaft of a low-speed motor (3 rpm).The fruits were filmed with a Logitech C920 camera. This is one of the most effective webcams on the market.A white sheet of paper has been used as background of the images.Due to variations in the lighting condition a dedicated algorithm of **flood fill** type has been written to extract image correctly from background.Total 18 types of fruits and vegetables have been used to identify in this framework.The 18 classes are given below:

- Cauliflower
- Dates
- Eggplant
- Ginger root
- Guava
- Lychee
- Orange
- Papaya
- Pomegranate
- Watermelon
- Apple
- Banana
- Lemon
- Mango

- Onion
- Pineapple
- Potato and
- Tomato

4.3 Impact Analysis

Impact analysis is an important aspect for implementing any new framework.It is necessary to observe whether it will do good or bad for the society as well as human ethics.The impact analysis is divided into two parts and discussed below:

4.3.1 Social and Environmental Impact

This proposed framework helps people to ensure balanced nutrition to keep up a healthy and diseases free life.This framework also helps to reduce obesity and overeating.It helps preventing eating foods those are not nutritious.By using this platform users can be at ease about their daily nutrition intake.So, it will do good for social as well as environment.

4.3.2 Ethical Impact

This proposed framework is completely ethical.It helps people maintaining a balanced diet as well as a healthy life style.It does nothing bad to any user as well as their surroundings.On the contrary, it keeps people's mind stable by ensuring their balanced diet.

4.4 Evaluation of Framework

The main purpose of this proposed methodology is to ensure balanced nutrition by recognizing image of fruits and vegetables using CNN.The main feature of this framework is divided into 3 major parts.Firstly, the framework detects image using deep convolutional neural network with validation accuracy of 97.8%.Then it calculates required calorie using Mifflin-St Jeor formulae.Other required vitamins and minerals are used from a local database.It then indicates about the lacking or consumption information for a particular user.Lastly, this framework can suggest people which fruits or vegetables to eat to keep a balanced nutrition based on the lacking nutrients.

By comparing with other frameworks we can see that, definitely this proposed framework is a better choice.In Platemate [19] it is shown that, it follows RFPM method [8] where it requires a special nutritionist to calculate nutrition intake.From NutriNet [20] we can see that, this framework is only good enough to recognize food and drinks.It does nothing more. The framework in [7] shows that, it can calculate nutrition intake by recognition of image using deep learning.From these functions of the above mentioned framework it is clear that the proposed methodology for Ensuring Balanced Nutrition using recognition and prediction of fruits and vegetables.

4.5 Evaluation of Performance

Performance of a system is measured by its ability to handle challenging situations in an effective manner.In this proposed methodology there are 3 challenging parts.

- Performance in recognition of fruits and vegetables.
- Performance in calculating nutrition intake for an individual.
- Performance in suggesting fruits and vegetables.

4.5.1 Performance in recognition

For recognition purpose of proposed methodology, CNN has been used as main backend engine.In this CNN architecture 4 convolutional layers and 2 fully connected layers have been used. In the output layer softmax activation function has been used while other layers along with input layer uses ReLU activation function.Performance of deep neural network like CNN can be measured using different metrics like model accuracy, validation accuracy, recall, precision, f1 score as well as relation among these metrics can be used to depict the overall performance for the recognition part of the proposed methodology.Precision, Recall and F1 score can be calculated using the following formula:

$$F1score = 2 * \frac{precision * recall}{precision + recall} \tag{4.1}$$

$$precision = \frac{TP}{TP + FP} \tag{4.2}$$

$$recall = \frac{TP}{TP + FN} \tag{4.3}$$

$$specificity = \frac{TN}{TN + FN} \tag{4.4}$$

$$FPR = \frac{FP}{FP + TN} \tag{4.5}$$

The value of these matrics for my proposed methodology is given in a table below: However, we can show relation of the accuracy score, loss score, precision score

Table 4.1: Different metrics for recognition model of proposed methodology

Method	Precision	Recall	Specificity	FPR	Accuracy
Proposed methodology	0.9788	0.9788	0.9987	0.001	0.9788
NutriNet [20]	0.8672	0.8672	0.8956	0.001	0.8672

and recall score by plotting the values during the training process. The plots are shown below to visualize the performance of proposed methodology very well.

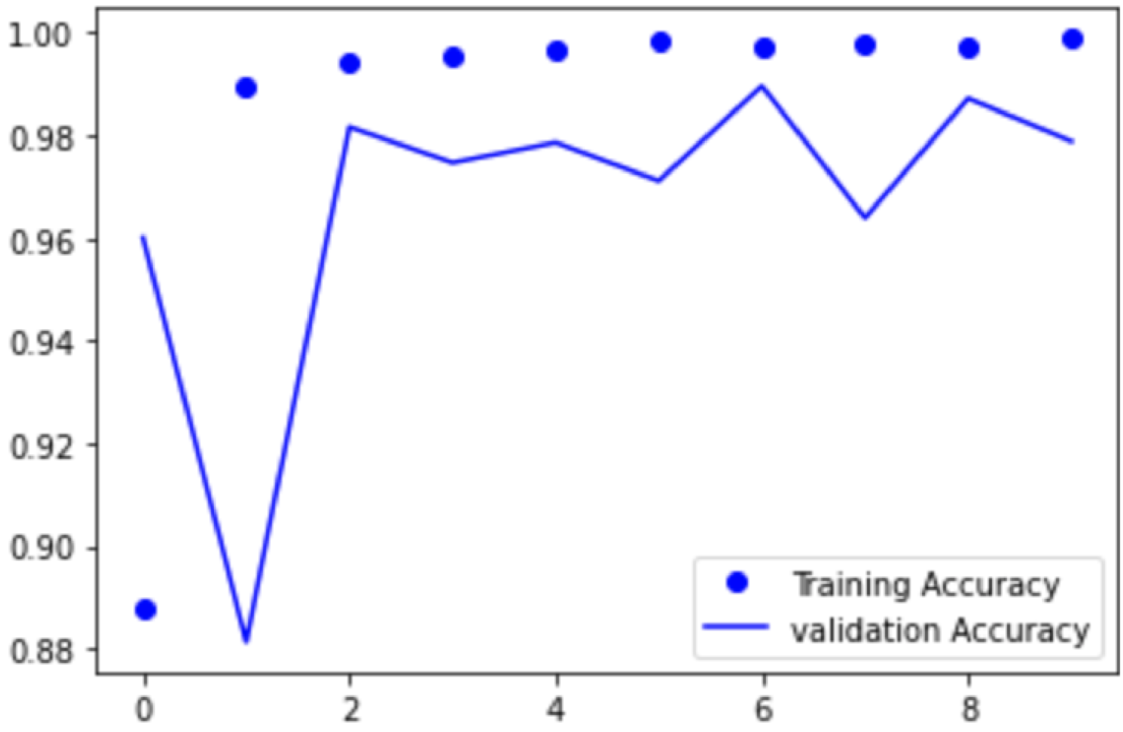


Figure 4.1: Training and Validation accuracy score

In figure 4.1 it is shown, how training and validation accuracy improves over time.

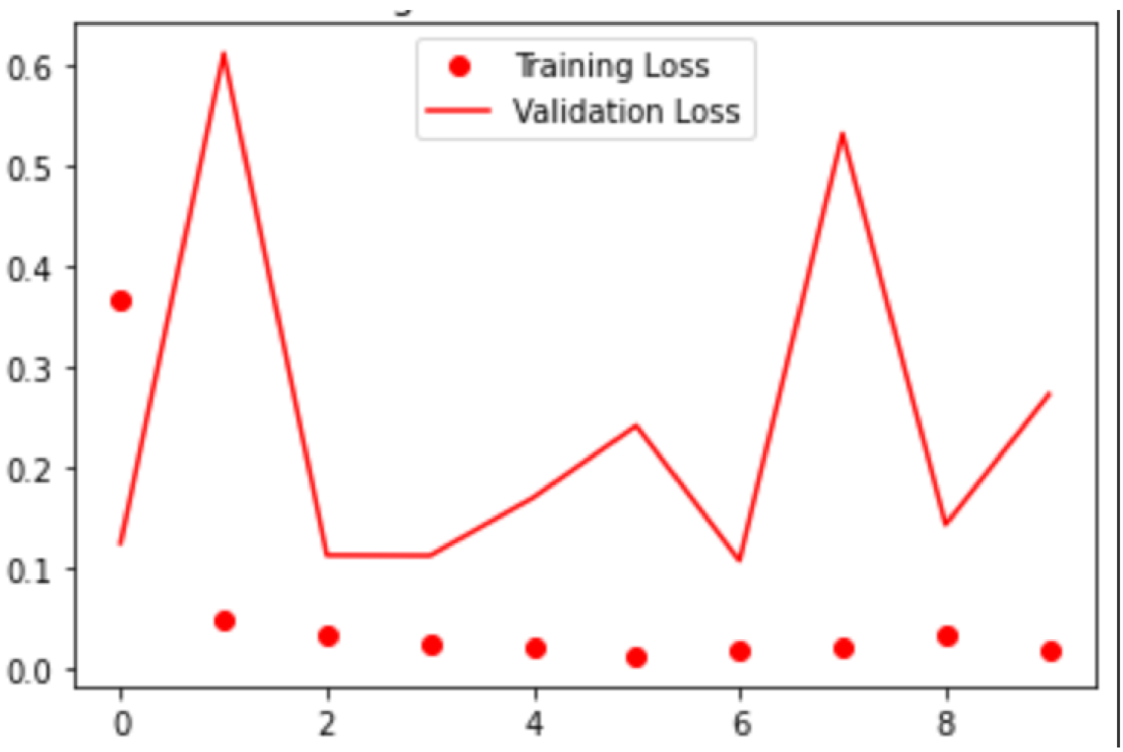


Figure 4.2: Training and Validation loss score

Figure 4.2 shows how loss decreases over time and improves efficiency of the model.

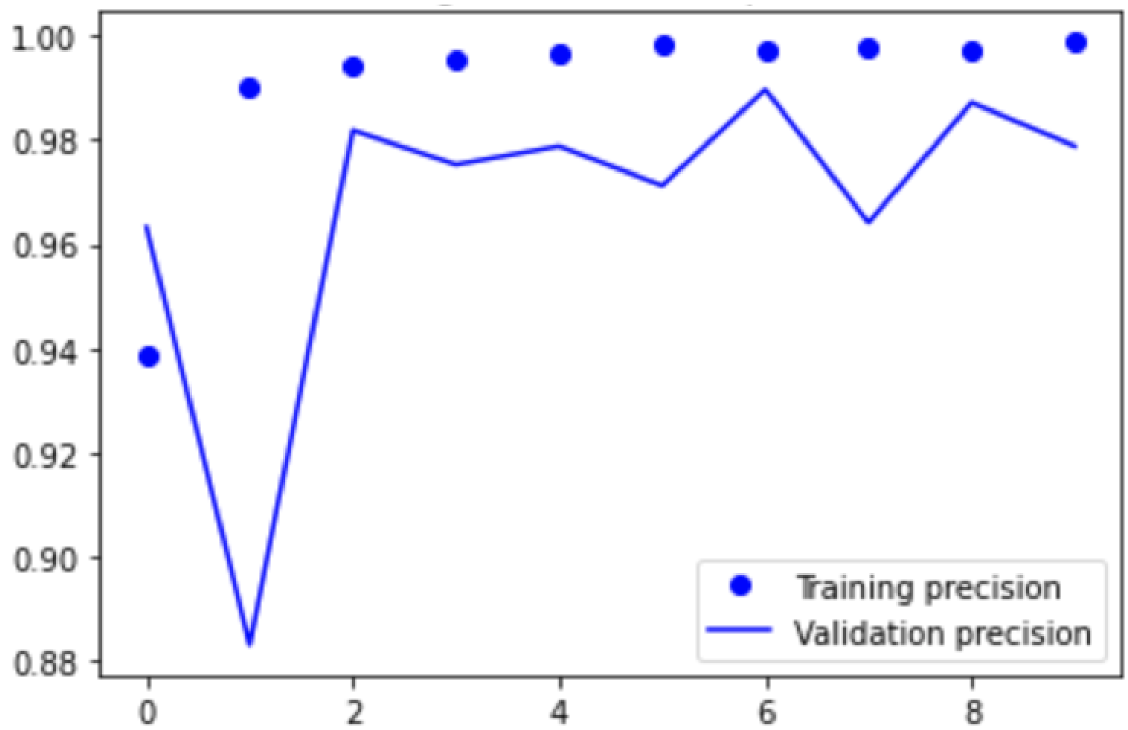


Figure 4.3: Training and Validation precision score

Figure 4.3 shows relation between training and validation precision score.

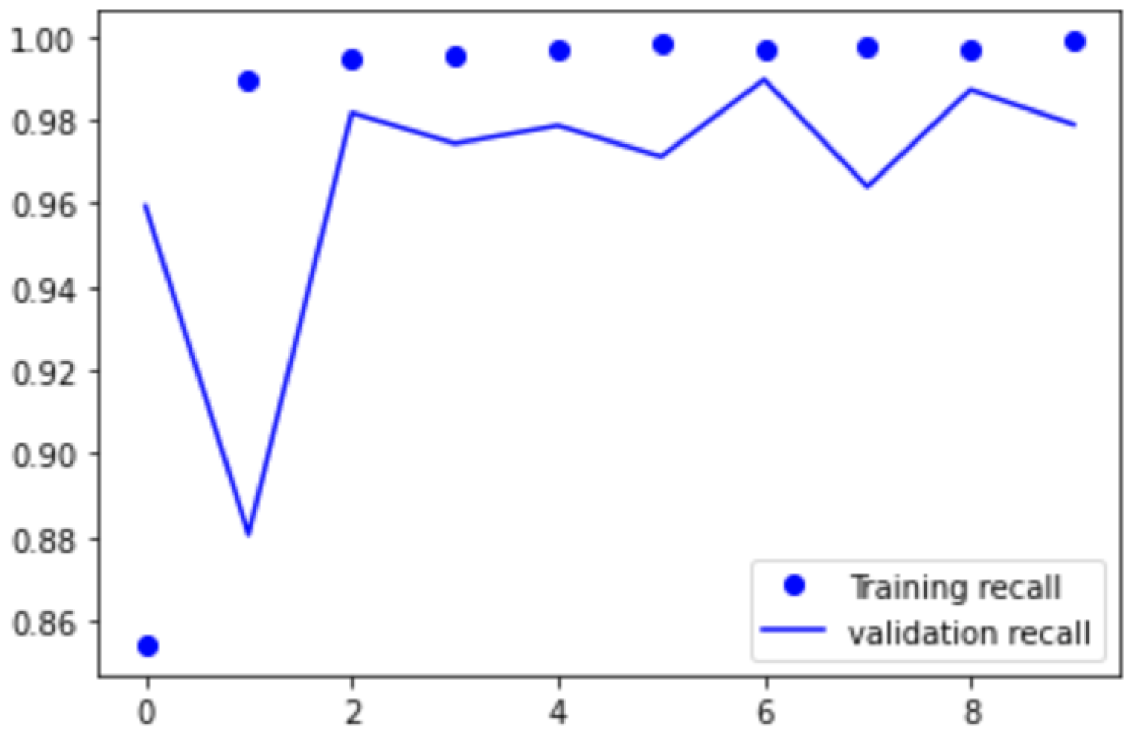


Figure 4.4: Training and Validation recall score

Figure 4.4 shows relation between training and validation recall score.

From the above table and figures it is easy to evaluate the performance of recognition section of my proposed methodology.

4.5.2 Performance in Nutrition Intake calculation

For calculating Basal Metabolic Rate (BMR) Mifflin-St Jeor formula has been used as it gives the most precise result.This formula depends on a person's age, weight, height and gender.By taking the masculine gender as 1 and feminine gender as 2, the main engine to calculate BMR looks like this:

```
print("1.Adult Men")
print("2.Adult Women")
print("Enter 1 or 2 to select your gender:")
gender = int(input())
print("Enter your weight in kg:")
weight = int(input())
print("Enter your height in cm:")
height = int(input())
print("Enter your age in years:")
age = int(input())
bmr = 0
if gender == 1:
  bmr = 10*weight + 6.25*height - 5*age - 161
else:
  bmr = 10*weight + 6.25*height - 5*age + 5
#print(bmr)
```

Figure 4.5: BMR calculation

In figure 4.5 if gender = 1, then it denotes to adult men and if gender = 2 or anything then it denotes to adult women.

Next, it is possible to calculate calorie intake by considering the exercise types.Depending upon the exercise types the calorie requirement will be different.The engine looks like this:

```
print("tell about your activity:")
print("1.little or no exercise")
print("2.lightly active (light exercise/sports 1-3 days/week)")
print("3.moderately active (moderate exercise/sports 3-5 days/week)")
print("4.very active (hard exercise/sports 6-7 days a week)")
print("5.extra active (very hard exercise/sports & physical job or 2x training)")
print("Enter 1,2,3,4 or 5 to select your activity")
activity = int(input())
required_calories = 0
if activity == 1:
  required_calories = bmr * 1.2
elif activity == 2:
  required_calories = bmr * 1.375
elif activity == 3:
  required_calories = bmr * 1.55
elif activity == 4:
  required_calories = bmr * 1.725
else:
  required_calories = bmr*1.9
print(f"Your daily required calories {required_calories}")
```

Figure 4.6: Calorie intake calculation

In fugure 4.6 it is shown that, depending on the daily activity BMR is multiplied by different numbers.Thus, proper calorie intake can be calculated.So, total calorie intake output looks like this:

```
1.Adult Men
2.Adult Women
Enter 1 or 2 to select your gender:
1
Enter your weight in kg:
65
Enter your height in cm:
178
Enter your age in years:
25
tell about your activity:
1.little or no exercise
2.lightly active (light exercise/sports 1-3 days/week)
3.moderately active (moderate exercise/sports 3-5 days/week)
4.very active (hard exercise/sports 6-7 days a week)
5.extra active (very hard exercise/sports & physical job or 2x training)
Enter 1,2,3,4 or 5 to select your activity
1
Your daily required calories 1771.8
```

Figure 4.7: Calorie intake output

After calculating daily calorie intake we can calculate other daily required vitamins and minerals from a local storage.Then, we compare these values with the nutritional values of a fruit or vegetables that is recognized by the system.The nutritional values of fruits and vegetables are also stored in a local storage.After comparing these two local storage, it can be calculated the daily lacking percentage of the nutrients for a particular user depending on his age and gender.The output looks like this:

```
How much apple(s) ? (amount in grams)
100
Calorie lacking 97.05515913466984%
Potassium lacking 96.85294117647058%
Vitamin A lacking 78.57142856666665%
Vitamin C lacking 94.88888888888889%
Calcium lacking 99.4%
Vitamin B6 lacking 100.00000000000001%
Magnesium lacking 98.75%
Protein lacking 99.46428571428571%
Sodium lacking 99.93333333333334%
you need to consume more 1713.8 calories, 3.2929999999999997g potassium,
0.0007071428570999999g vitamin a, 0.0854g vitamin c, 0.994g calcium, 0.0013g
 vitamin b6, 0.395g magnesium, 55.7g protein, 1.499g sodium
```

Figure 4.8: Nutrients lacking indicator

In figure 4.8 it is shown that, first we have to input the amount of the fruits and vegetables that just was recognized by the system.Then the comparison happens between the two local storage according to the equation 3.9.Then, a lacking percentage of the nutrients can be shown like the output.

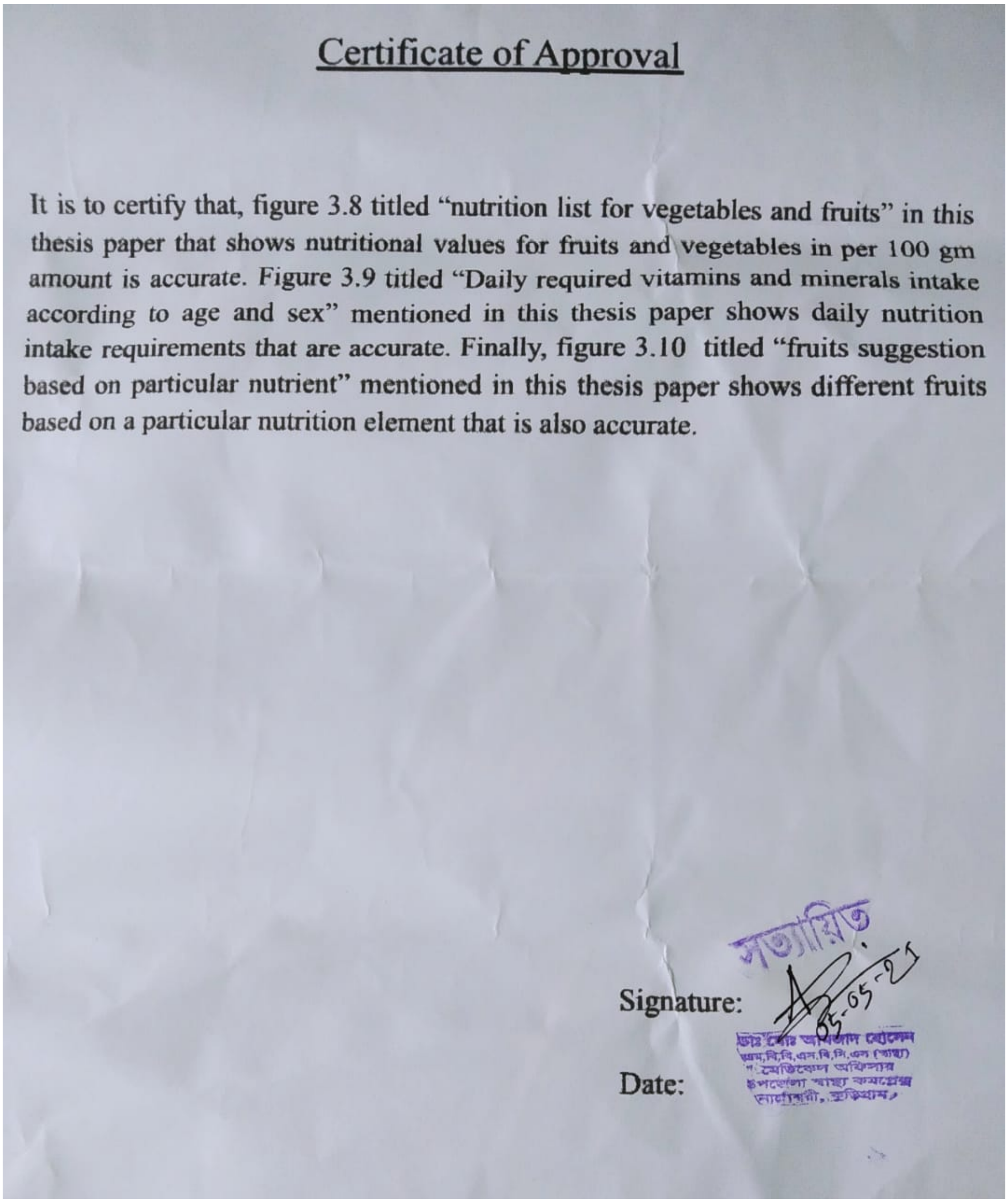
4.5.3 Performance in Suggesting Fruits and Vegetables

From figure 4.8 it is shown that, in the lower part of the image, it is possible to detect the quantity of the nutrients that should be taken by an user.Then the data is prioritized according to the lacking of the nutrients.The more lacking, the higher priority is set.The top 3 priority is then considered.Fruits and vegetables are then suggested based on the priority nutrients using figure 3.10. After calculating lacking percentage, now the framework is ready to make prediction. From figure 4.8 it can be seen that, the most lacking is of protein, vitamin B6 and sodium. So, this framework will predict the fruits or vegetables that are enriched with protein, vitamin B6 and sodium.The output will look like this:

```
The least taken nutrients are: Protein, vitamin B6, sodium,
You should eat: guava, jackfruit, potato, banana, tomato, cucumber
```

Figure 4.9: Fruits prediction of framework

The above calculation has been done using figure 3.8, figure 3.9 and figure 3.10. The authentication certificate about these figures is attached below:



Certificate of Approval

It is to certify that, figure 3.8 titled "nutrition list for vegetables and fruits" in this thesis paper that shows nutritional values for fruits and vegetables in per 100 gm amount is accurate. Figure 3.9 titled "Daily required vitamins and minerals intake according to age and sex" mentioned in this thesis paper shows daily nutrition intake requirements that are accurate. Finally, figure 3.10 titled "fruits suggestion based on particular nutrient" mentioned in this thesis paper shows different fruits based on a particular nutrition element that is also accurate.

Signature:

Date:

Figure 4.10: certificate of authentication

4.6 Conclusion

This chapter shows the result of the proposed methodology and performance in details.Also, some outputs have been shown to prove it's performance.In the next chapter, conclusion on this framework is drawn.

Chapter 5

Conclusion

5.1 Conclusion

Developing a framework that ensures balanced nutrition by recognizing an image is a life changing event.This framework also suggests or predicts necessary fruits and vegetables.By using this framework the users can be at ease about their nutrition intake.

Some difficulties have been issued regarding this framework in Chapter 1.Also, some motivation as well as application have been outlined in this chapter.To lead a healthy life there is no alternative to balanced nutrition.To ensure balanced nutrition a basic framework overview has been discussed also.Some related system and platform like "Snap, Eat, Repeat", "NutriTrack", "NutriNet" have been discussed briefly.Also, their limitations have been outlined.However, there are many platforms those are used to recognize image.Calorie Measurement using deep learning and another platform called "Platemate" have been discussed in literature review chapter.

Methodology for "Ensuring balanced nutrition by recognition and prediction of fruits and vegetables" has been discussed in Chapter 3.The CNN model architecture has been shown.Different types of layers such as convolutional layer,pooling layer and activation function such as ReLU and softmax have been discussed.Fully connected layer has been used at the end of the CNN architecture.Then, BMR calculation formula has been used that uses age, height, gender and weight parameter.After considering some exercise types, required daily calorie intake has been calculated.Two local storage has been used to indicate nutrition lacking.One storage holds information about nutrients present in each 100gm of fruits and vegetables of 18 types.Other storage holds information about daily nutrition requirements for a person.This storage is created based on age and gender varying between 6 months and 51+ years.Then, a prediction system is built upon calculating the nutrition lacking.

Result of this proposed methodology and framework performance has been discussed in Chapter 4.This chapter also details about the framework evaluation and performance evaluation.Performance is evaluated using accuracy curve, loss curve, precision curve, recall curve, f1 score, specificity etc.Also, some output snapshot has been shown to prove the framework's accuracy.

5.2 Future Work

As ensuring balanced nutrition by image recognition is a burning question, so there is always a scope of improvement.The current methodology to work properly the amount of fruits and vegetables must input manually.This is a fact of improvement.In future, it will be tried to measure the consumed amount automatically by just taking a single snapshot using deep learning neural network.This proposed methodology will be implemented in all available mobile platform like android and iOS as the number of people holding hand-held devices are increasing dramatically.First, this platform will be a web application so that everyone in this earth can access to the system.Then, android and iOS API (Application Programming Interface) will be developed.

References

[1] W. H. Organization *et al.*, *Http://www. who. int/mediacentre/factsheets/fs311/en/index. html*, 2010 (cit. on p. 1).

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