

PROFICIENT EXPLORATION OF MALNOURISHMENT WITH MACHINE LEARNING BY CNN PROCEDURE

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ABSTRACT

In this paper we are expanding perception of disease finding of human body using nail image of human fingers and analyzing data from the image of elementary of nail color. The technique of disease detection is as follows: The involvement to the system is a person nail image. The system will process an image of nail and extract feature of nail which is used for disease diagnosis. Here, first training data is organized using Machine Learning from nail image of patient of specific disease. A feature extracted from input nail image is compared with training data set. In this project we found that color feature of nail image are correctly matched with training set data. Image processing is a process to convert an image into digital form and perform some operation on it & order to get an enhanced image or to extract some useful information from it. So, its execution of nail color Analysis through computer is a superior technique as compared with human eyes. This system would be cooperative for the patient, as patient need not to be present in person or if the doctor is not available for consultation purpose consequently just by receiving patient's nail image the doctor can diagnose the symptoms and write appropriate treatment for the disease that is being analyzed.

Keywords: disease detection, nail image, image processing, malnutrition

1. INTRODUCTION

In this research system analyses a person's nail and determines whether or not they have an illness, even though they are well. Nail colour (average RGB) value is used as a nail feature for disease prediction. Subjectivity and resolving capacity are more accurate for this model than with the human eye. This can provide a more precise outcome by using a machine learning algorithm to classify human health conditions [5]. This system is use to the any patient to analysis the DISEASE for identify specific disease patient. The colour attribute of a human nail will be extracted and used in the classifier. The image recognition technology is relying on human fingernail examination. a lot of illness can be discovered by analysis of the human fingernails Instead of the photography-based method, an image of a person using a camera is used. Our nail images have now been submitted to our system, and are assigned to a region of interest based on hand-picked user photos. Features such as nail color are extracted Basic training data were used to determine the hue of this nail polish. The prediction model is useful to them at the beginning stages of its evolution

2. TYPES OF MALNUTRITION & CNN OPERATION

2.1 Protein-energy malnutrition: Protein-energy malnutrition (PEM) is a form of malnutrition considered by a variety of conditions that arise in varying volumes as a result of concurrent shortage calories. There are three levels of severity: mild, moderate, and severe. PEM is very popular among both children and adults around the world, and it causes six million deaths per year [9]. PEM is most often found in hospitals, where it is related to cancer, or in elderly people in developing countries. When there is a waste of protein resources, such as in chronic renal failure or cancer cachexia, PEM can be secondary. The term "protein-energy malnutrition" (PEM) refers to a state of general malnutrition and energy shortage. Extreme PEM is used in a variety of therapeutic situations, from open kwashiorkor to heavy marasmus, where the body's nutrition and energy requirements are not fulfilled [8].

2.1.1 Acute malnutrition (also known as “wasting” or “starvation”): Acute malnutrition is a life-threatening emergency. Acute malnutrition affects 55 million children under the age of five globally, with 19 million of them suffering from severe acute malnutrition. Hunger claims the lives of 3.1 million children per year. The human body requires energy and available nutrients [7].

2.1.2 Chronic malnutrition (also called “stunting”): Chronic malnutrition, also known as short-term malnutrition for era, results in chronic malnutrition due to constant illness, poor treatment or nursing, low salaries and poor food. Stunting will disrupt brain function, organ development and immune system activity, all of which will lead to severe potential health problems. Chronic malnutrition is also a primary driver of infant mortality, although the direct cause of death is less likely. However, early childhood chronic malnutrition has long-lasting implications for a wide range of other outcomes such as education, potential capacity for employment, income earning and chronic illness, both having significant effects on individual and social developments.

2.2 Micronutrient deficiencies (also known as “hidden-hunger”): Micronutrient deficiencies are described as a lack of necessary vitamins and minerals that the body requires in limited amounts to grow and develop properly. Important micronutrients (vitamins and minerals) including vitamin A, copper, zinc, and iodine are in short supply. Micronutrient shortages are a major public health problem that affects important developmental outcomes such as poor physical and behavioral growth of children, disease vulnerability or exacerbation, mental retardation, blindness, and general lack of efficiency and ability. The health consequences of a micronutrient deficiency are not quite as severe as those of an energy protein deficiency. 'Hided hunger' is another term used to describe it. Micronutrients are very small quantities of vitamins and minerals required by the body. However, their effects on the health of a body are important and their deficiency can create extreme and even life-threatening conditions. They perform a variety of functions, including allowing the body to generate enzymes, hormones and other substances necessary for normal growth and growth.

Iron, vitamin A and iodine deficiencies are the most common in the world, particularly among children and pregnant women. The overwhelming burden of micronutrient deficiencies lies with the low and middle-income countries. Micronutrient shortages can lead to noticeable and hazardous conditions for health, but can also result in less clinically significant energy, mental clarity and overall ability reductions. This can lead to less schooling, lower work efficiency and an increased risk of other conditions and diseases.

2.3 Nutritional deficiencies: Many vitamins and minerals are required by the body, and they are essential for both body growth and disease prevention. Micronutrients are the minerals and vitamins that make up our bodies. Since they do not grow spontaneously in your body, you must exclude them from your diet. The body is considered a nutritional deficiency if not absorbing or obtaining the nutrient it needs from food. Deficiencies may trigger a range of illnesses. This may include stomach issues, skin abnormalities, smooth or deficient bone formation, and dementia. Depending on your age, the amount of each nutrient you can eat. In the USA, many foods that you buy in the food shop are enhanced by nutrients that are required in order to prevent nutritional deficiency, such as cereals, bread and milk. But your body often cannot consume those nutrients even though you eat them. One of the nutrients your body requires may be deficient. Continue reading to learn about and how to prevent common nutritional deficiencies.

3. CNN Operation

CNN (ConvNet) is a deep neural network class widely used in visual imaging. Also known as SIANN, it scans secret layers and translation invariance features dependent on convolution kernels' joint weight architecture. Picture, image grading, image segmentation, medical image analysis, natural language processing, brain/computer interfaces, and time series are only a few examples [5]. CNNs are multilayer perceptron structures that have been regularized. This networks' "total connectivity" helps them to overfit results. Weight variants are typical methods of control where the loss function is minimised when connectivity is arbitrarily diminished. CNNs have a distinct approach to regularisation, relying on the hierarchical nature of their data to piece together more complicated patterns using smaller and simpler filter patterns. As a result, CNNs are at the very bottom of the connectivity and complexity scale [13].

Define the CNN

In contrast to a traditional neural net global pattern, a CNN learns precise patterns using image raw pixel filters. To create a CNN, you must first define:

1. **Convolutional layer** Apply a set of filters to the function map. After convolution, you must use the Relu activation function to add non-linearity to the network.
2. **Pooling layer** After convolution, the next step is to downsample the max function. The aim is to reduce the feature map's dimensionality to prevent overfitting and improve measurement speed. The traditional approach is to divide the maps into subregions (typically 2x2) and keep only the highest values.

3. Fully connected layers All neurons in the following layers are connected to those in the previous layers. The convolutional layers' characteristics can be used by the CNN to define the label.

3.1 ReLU Layer

We choose to do this because images aren't really straight. Any image contains a variety of non-linear features (e.g. the transition between pixels, the borders, the colors, etc.). The rectifier eliminates still more linearity from the picture to compensate for the linearity we may introduce as it is transformed. The Rectified Linear Unit is not a stand-alone neural network component. This is a step that was not discussed in the previous tutorial's convolution process. While some teachers and authors address the two steps separately, in our case, we will consider them to be part of the first stage in our strategy.

3.2 Pooling

Max pooling tells the convolutional neural network that they are all the same, including the inconsistencies we mentioned earlier. The network must buy a property known as "spatial variance" in order to do so. This property enables the network to find the goal in the image regardless of variations in the image's colours, heights, angles, or other variables. Convolutional layers are used to build feature maps in a convolutional neural network, which summarise the existence of these features on the input. Convolutional layers have shown to be highly accurate, and stacking them in deep models helps input-oriented layers to learn low-level features (e.g. lines), whereas deeper layers of the model learn higher-order or abstract features like shapes or items. This move is straightforward. The aim of pooling is to reduce the input picture's dimensionality. The measures are taken to reduce the process' mathematical complexity. The network has less weight to calculate as a result of reducing dimensionality, which prevents overfitting. At this stage, you must decide on the size and location of the transfer. As a standard form, the full value of the function map is used to pool the input image. Please see the diagram below. The "pooling" submatrix is screened, and the highest possible value is retrieved. The "pooling" procedure.

3.3 Flattening

For each function chart patch, determine the maximum possible value. The result of the group layer and the creation of sampled or grouped feature maps is a summarised representative of the features in the proposal. They are helpful if they add minor modifications to the functionality of the input observed by the convolutionary sheet to an integrated semantic map at the same time. This more pooling strength applies to the invariance of the model in local translations.

3.4 Pooling

After flattening, the input data is further analysed, a method known as pooling, by a long vector that moves across the artificial neural network. Each channel of the function map must

have a two-dimensional filter slid over it, and the features within the filter region must be summed.

For a feature map having dimensions $n_h \times n_w \times n_c$, the dimensions of output obtained after a pooling layer is

$$(n_h - f + 1) / s \times (n_w - f + 1) / s \times n_c$$

where,

n_h - height of feature map

n_w - width of feature map

n_c - number of channels in the feature map

f - size of filter

s - stride length

A common CNN model architecture is to have a number of convolution and pooling layers stacked one after the other.

3.5 Full Connection

This part brings everything we've learned so far together. You'll discover how Convolutional Neural Networks function and how the "neurons" that are eventually created will learn to recognise images by doing so.

The entire connection phase has three layers, as seen in the diagram below:

- Input layer
- Fully-connected layer
- Output layer

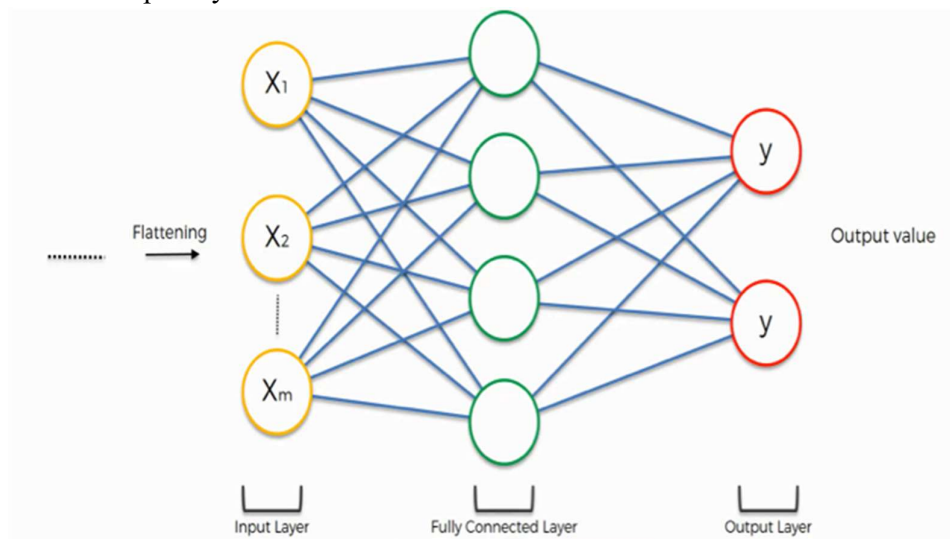


Figure: Full Connection Setup

The middle layer was formerly referred to as the "secret layer" in artificial neural networks,

but it is now referred to as the "fully connected layer" in convolutional networks.

3.6 The Full Connection Process

The final move, as in the previous tutorial, is to build a conventional artificial neural network. The neurons of the previous layer are bound to the neurons of the next layer. The number in the input picture is described using a softmax activation function. we begin with an input image that we turn, pool, flatten, and then move through an artificial neural network. The neural network makes its predictions at the end of this channel. The network, for example, assumes that the image is of a skin with an 80% chance of becoming a skin, but it is really a cat. In this case, an error must be determined.

3.7 Summary

The procedure is which follows:

- We'll start with a picture.
- We use picture filters or maps of a convolutional layer to build a convolutional layer.
- The rectifier feature is then used to break up the image's linearity.
- The picture is ready for a grouping step, which will give our convolutional neural network "spatial invariance."
- Once we've done pooling, we'll have a pooled feature chart.
- We flatten out our pooled function diagram before putting it into an artificial neural network.

3.8 SoftMax & Cross-Entropy

The Softmax function is a "soft" version of the Max function. Instead of choosing a maximum sum, it divides the entire with several other smaller items, with the maximum item being the largest proportion of the distribution. This softmax function property creates a probability distribution that can be used in classification activities with probabilistic interpretation. The distance between what the model feels might be the output distribution and what the initial distribution is seen by cross entropy. $H(y,p) =$ mentioned below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below $H(y,p) =$ listed below (π) A typical squared error alternative is cross-entropy calculation. When the performance is a probability distribution, it's used to understand node activation as a possibility that some hypothesis may be right. It's then used in neural networks with softmax activations in the output layer as a loss feature [15].

4. STATISTICS ANALYSIS & TRIAL WORK

We would measure firmly in this project by focusing on illness recognition of a human finger nail picture and evaluating the details obtained from the fundamental image of nail colour. During this process, the disease detection protocol may be as follows: A image of a human nail is used as the computer data [24] . The computer can analyze a nail picture as well as a nail extraction mechanism in order to diagnose a disease. The first coaching encounter is a

ready maltreatment Machine Learning from the nails of a patient's true disease. The knowledge set is related to a feature derived from the representation of the input nail. During this system, it seems that the nail picture's colour attribute is matched with coaching experience [11].

The colour characteristic of a human nail picture will be derived for disease prediction in this project scheme. The approach relies on pattern detection and is based on human nail colour analysis. A host of diseases may be diagnosed using human hand nails. This unit's camera takes a view of a human nail. The picture is transferred to our computer, and the problematic nail is manually selected from the image. The chosen region is then examined further to exclude characteristics such as nail colour [14]. This nail's colour feature corresponds to simple disease prediction training results. As a result, the approach is effective in the early stages of prediction.

The method depicted below uses image recognition to include a human nail diagnostic system. The early diagnostic method relies heavily on machine learning. The computer block diagram depicts the whole structure in detail. With the help of GUI, we get the results for GUI framework code in this process (Graphical User Interface). The photo is taken with a digital camera or a mobile phone camera. This file can be used in any format, like jpeg, as an image input. To process the image, we must first break it into the appropriate block in order to extract its characteristics [22].

design process mainly three modules are use

- Patient module
- Admin module
- Processing module

Overview of system module:-

- **Patient module:** To monitor diseases, upload a photo of the patient's malnutrition to this module. Without the doctor's advice, the patient's well-being is critical or may not pose a danger to the illness. This module defines the patient's characteristics, which are used to categorise and characterise the patient under investigation. This module includes patient characteristics that are common to all patient studies and are needed for the analysis of Composite Instances. For the procedure in this module form, take a picture of the nail and face.
- **Admin module:** Using the medical backend, the admin trains the picture data collection for the analysis and comparison of prospective patient files. The Admin module allows the system overseer to establish up the structure backend and perform simple system setup, such as specifying predefined drop-down fields, class times, and so on. View real-time

data tables, view/edit individual records, validate your survey before fielding, import incomplete/complete password lists, shutdown the survey, and reset your survey.

- **Processing module:** After a patient takes a snapshot, the suggested CNN algorithm uses the identification approach on the image to determine whether or not the patient is malnourished. Production occurs as data is gathered and translated into usable material. It is important to perform the data analysis correctly such that the end output or data creation is not harmed.

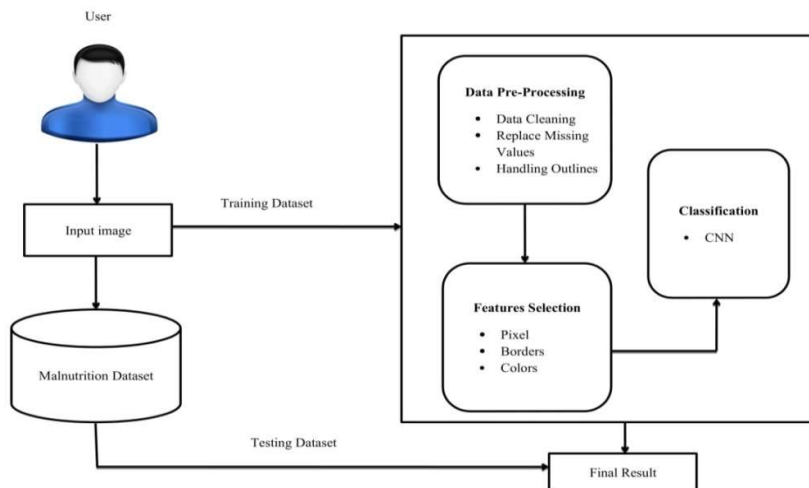


Figure: - System Architecture

4.1.1 Input Image:-

The treatment begins with the customer taking a photograph of the patient's nails or scalp. The input picture from the data collection is transformed into an assembled image, which ensures that the pixel values are summed in a known rectangular frame. The input element with the type-attribute "image" is a graphical button that is a common image and when pressed, submits the form to which it belongs. The coordinates of the click are sent in the form when the form is sent, which is a unique function of picture buttons. This may be helpful for allowing users to pick a picture region while downloading a form, for example. Writers should be aware, though, that visually disabled and non-supporting browsers can have trouble uploading the form correctly.

4.1.2 Malnutrition Dataset

Malnutrition datasets are simply databases containing all patient records, including such details as age, illnesses, nail and skin images. It also includes a dataset and test data collection that conducts operations such as creating a safe and unhealthy club picture, as well as healthy and unhealthy images. Data compilation on malnutrition The built model is tested using a test (or validation) chain, and a model-building training kit is implemented. The models are used to simulate unexpected results, known as the test collection. Like you have already said, the

data is split into a train and a test array in order to check accuracies, accuracy and testings for the training dataset.

4.1.3 Processing system

Our algorithm for prediction is provided by a software that also changes the weights of the neural network. Our algorithm is designed to fulfil the training sets' requirements. During the cross-validation process, we produce many algorithms for assessing their accuracy. The test results array contains the whole testing dataset. You may extract features and learn to fit a standard, for example. Our model is basically trained and adjusted to the parameters, while the test data is only used to determine model performance. The model will use the training data's performance, while the test data is unpredictable data that must be expected. A data processing device is made up of machines, humans, and processes that produce a collection of outputs in response to a set of inputs. The inputs and outputs are interpreted as records, information, expertise, and so on, depending on the interpreter's relationship with the machine. A data or storage (code) retrieval system is commonly referred to as a knowledge system. Choosing the correct parameters for the estimator during the validation test is critical. We might make a train package out of the training set. The validation test results can be used to train the model (for instance, changing parameters, classifiers). This aids us in obtaining the right model.

4.1.4 Data pre-processing

Preparing and adapting raw data for use of a machine learning model is known as data preprocessing. It's the most important step in building a machine learning model. When working on a learning machine project, we don't always come across neat and formatted results. It's often crucial to tidy up and format information before using it. Data preprocessing operations are used to do this [7]. Real-world data also includes sounds, missing values, and even an unusable format that cannot be directly included in computer models. Data preprocessing includes tasks like data cleaning and training for a machine learning algorithm, both of which increase the model's accuracy and performance. Images are available in a range of shapes and sizes. They even come from a lot of countries. Those photographs, for example, are "true pictures," implying that they were captured in the modern world and are vibrant. All image details must be pre-processed to prepare for any of these differences. The most popular encoding format, RGB, is used to encode several 'natural images.' The first step of data preprocessing is often the development of identical-sized images. Let's take a peek at how to change the shape and design of your images [21].

Data pre-processing involves following steps:

Step 1: Getting the dataset

The first step in creating a machine learning model is to obtain a data collection that is entirely based on data. As a model for deep learning. The data collection refers to the data collected in

a suitable format regarding a particular issue. For example, if we were to build a business learning computer model, the dataset would be different from the data set used for a patient with a liver. As a result, each dataset is distinct from the others.

Step 2: Importing libraries

Any predefined Python libraries must be imported in order to preprocess data utilising Python. Any activities include the usage of these repositories. For preprocessing info, there are three key libraries.

Step 3: Importing datasets

The data sets we collected for our machine learning research must now be imported. However, before importing a dataset, we must make the existing directory a functioning directory.

Step 4: Finding Missing Data

The next step is to deal with the datasets' missing results. If some of the data in our dataset is incomplete, it can cause a huge issue for our learning model. As a result, the dataset's missing values must be addressed.

Step 5: Encoding Categorical Data

Categorical data, such as our data collection, contains such categories; two categorical variables are purchased, region, and country. Since a machine learning algorithm is solely based on statistics and quantities, difficulties can emerge when building a model if our dataset contains a categorical element. These categorical factors must be converted to numbers as well.

Step 6: Splitting dataset into training and test set

We divide our data set into a training set and a test set during the preprocessing of machine learning data. This is a crucial phase in data preprocessing because it allows us to increase the reliability of our machine learning model. Assume we've prepared our machine model with one collection of data and then tested it with a new set of data. Our model will then struggle to comprehend the distinctions between the styles.

Step 7: Feature scaling

The final phase in the preprocessing of machine learning data is feature scaling. It's a method for standardizing the independent variables in a data set within a certain range. We put our variables within the same spectrum of feature scaling such that no one variable dominates the other.

5. RESULT & DISCUSSION

Method 1:

Image processing is used in this method to create a disease detection mechanism dependent

on human nails. Machine learning is at the forefront of an early stage diagnostic device. The whole structure is shown in the computer block diagram. In this framework, we get the result using the GUI (Graphical User Interface), and only GUI device code is needed to execute it. The picture is captured with a digital camera or a mobile phone [13].

The buttons are then created using the GUI, and we get our result by removing its features and calculating its RGB value, which is the Red, Green, and Blue plane value. So we would calculate the parameters in order to allow a relation. We may precisely equate twelve different measurement parameters. Then we collect data from a wide range of patients as well as healthier people, then we set a realistic disease cap. Finally, we use the identify button to equate our train data collection to our input picture parameters and calculate the percentage of this image that meets the limits of proper patient diseases.

Method 2:

The step in the classification using proposed work as follows:

Algorithm TE Classification

Step 1: Begin

Step 2: Build the list of image or start the training

Step 3: Give path for storing bottleneck Values

Step 4: provide inference to image or create bottleneck value

Step 5: Create folder for all images of bottleneck values

Step 6: Create bottleneck value for every single image.

Step 7: Create new softmax layers & fully connected layers.

Step 8: Test the new image

Step 9: End

We are developing a concept for disease detection in the human body using human finger nail images and analysing data from a single nail colour picture in this project. The disease detection protocol for this project is as follows: A photograph of a person's nails serves as guidance to the device.

A image of a nail would be examined by the robot in order to extract nail features that can be used to diagnose disease. The first training data were collected using Machine Learning from a nail picture of a patient with a specific illness. The training data set is compared to a function extracted from the input nail image. We discovered that the colour characteristics of a nail image are correctly aligned with training set data in this experiment.



Figure: Data collection sample

The picture is captured with a digital camera or a mobile phone. This picture serves as the input and can be in any format, like jpeg. To begin processing, we must first crop the picture into the required block to delete the image's attributes [35].

Graph

Both for the validation and training curves, the cost (loss) feature is high and does not decrease with the amount of iterations, and we can just use the training curve and ensure that the loss is high and does not decrease, to see whether it's under fitting loss curve used under the,

- baselines
- real-world indicators
- for regression questions

- total failure
- additional indicators for classification issues

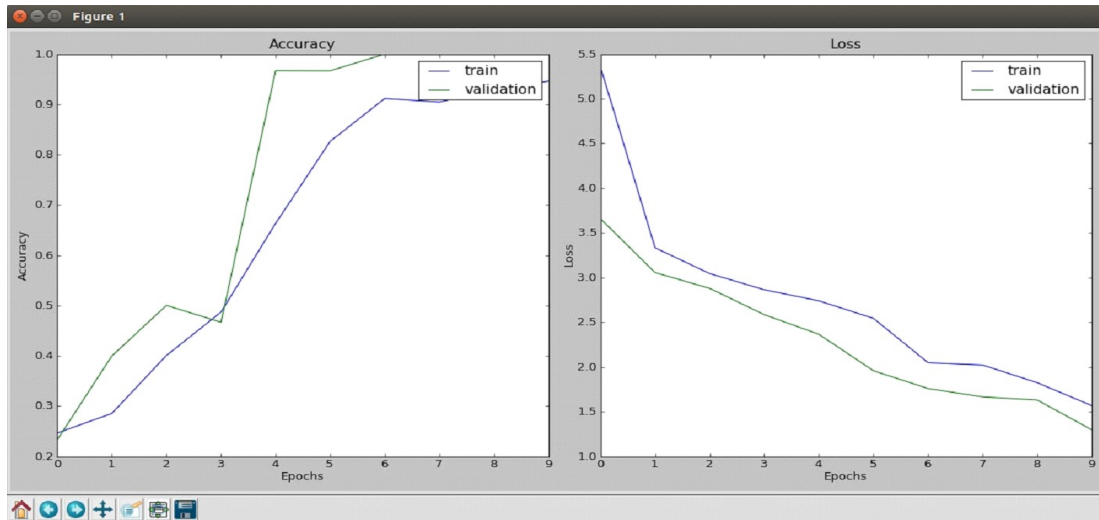


Figure: Result of Accuracy & Loss Graph

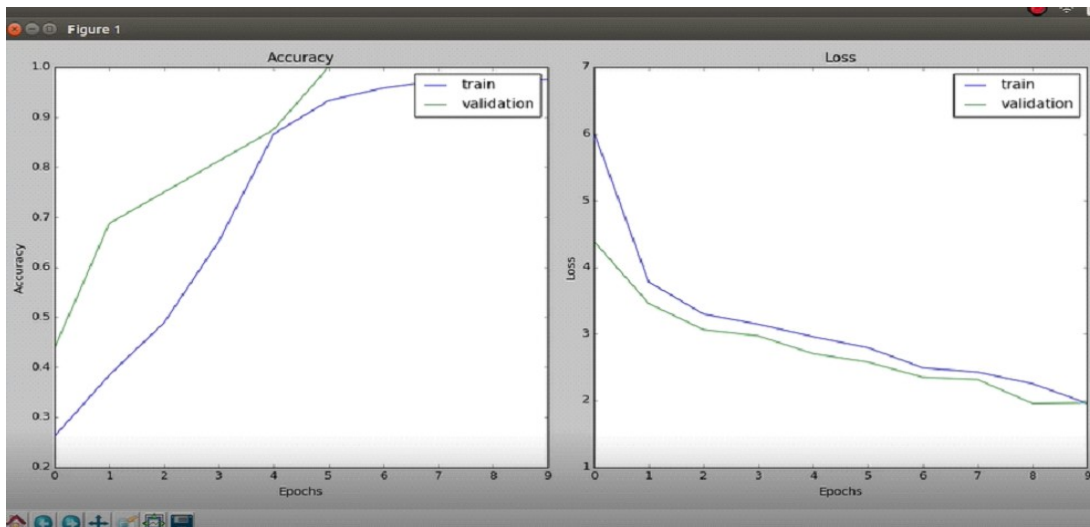


Figure: Result and analysis

6. CONCLUSION

The machine analyses a person's nail and decides whether or not they have an illness, even though they are well, according to the proposed scheme. The average RGB value of the nail is used as a nail function for disease prediction. This model is more realistic than the human eye in terms of subjectivity and resolving power. When utilising a machine learning method

to identify human health problems, this will produce a more accurate outcome. To predict disease, this project will use an abstract colour feature of a human nail picture. The framework is based on human nail colour analysis and relies on image recognition. The fitness of an individual may be determined by looking at their nails. A camera in this system is used to get an image of a human nail. The picture is uploaded to our device, and the nail area's region of concern is manually picked from the image. Additional therapy is then applied to the selected region in order to minimise nail features such as colour. In this process, malnutrition, the dataset collects data from the user module and stores it in the database. This knowledge is crucial for deciding whether or not the topic is malnourished. The testing dataset is often used, and is moved on to the data preprocessing modules.

The colour of human nails may be used to diagnose a variety of diseases in the healthcare sector. A white spot here, a rosy dot there, or a wrinkle or projection here and there may both be symptoms of illness. Problems of your stomach, lungs, or heart can be seen by your nails. Doctors look at a patient's nails to help diagnose an illness. A person's pink nails normally indicate that they are in good health. The approach is based on human nail colour analysis and relies on image recognition. Human fingernails may be used to diagnose a variety of diseases. A human nail picture is used in the dataset and is included in this process. After receiving the submitted file, our device selects the region of interest from the nail area manually. After that, the chosen region is treated to extract nail characteristics including colour. This nail colour function is then matched using a basic matcher algorithm for disease prediction. As a consequence, the technology will aid in the early detection of diseases. In the literature review, certain diseases and their related nail color changes were reported.

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