Malnutrition Detection Analysis and Nutritional Treatment using Ensemble Learning

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Abstract- Malnutrition is a condition that arises when an individual's diet contains excessive amounts of certain nutrients or insufficient amounts of one or more of the essential nutrients. The proposed system uses an ensemble learning model of the CNN, the transfer learning algorithms such as Inception-v3, VGG16 and VGG19 were combined together with the help of ensemble learning to enhance classification, prediction, function approximation, etc. The model takes input images and classifies them as normal, wasting, stunting, and obesity. The goal of the proposed system is to identify malnutrition and its types and provide treatments for each category and ways to prevent malnutrition which will assist in lowering the danger of mortality, health and physical problems by using the appropriate treatments or precautions. In conclusion, the proposed system is a significant step towards identifying and treating malnutrition effectively. By using ensemble learning algorithms, it can accurately classify different types of malnutrition and provide appropriate treatments to those affected.

Keywords: Analysis, CNN, Deep learning, Ensemble learning, InceptionV3, Nutritional, Malnutrition, VGG16, Vgg19.

1 Introduction

Malnutrition is a serious health issue that affects millions of people worldwide. It results from the inadequate intake of essential nutrients from food, causing various health issues such as weakened immune systems, stunted growth, and an increased risk of infections. Early detection and treatment of malnutrition are essential to prevent the long-term consequences of this condition. The conventional methods for detecting malnutrition include physical examination, body weight measurement, and blood tests. Nevertheless, these methods are often costly, time-consuming, and may not always produce precise outcomes. As a result, there is a necessity for a more dependable and efficient approach to identifying malnutrition.
Deficiency of consumption of different nutrients can lead to malnutrition which is one of the main health issues that persist all over the world. Underlying child mortality and morbidity can be considered one of the major factors for malnutrition in infants. Undernutrition is thought to be the cause of about 45% of fatalities in children who

belong to the age group of 0-5 years. According to a survey 42.5% of children who are under the age of four to five in India were underweight, 19.8% were wasted, 6.4% were seriously wasted, and 48.0% were stunted. According to the National Family Health Survey (NFHS–4), 35.8% of children were underweight, 21.0% were severely wasted, and 38.4% were stunted.

Although stunted and underweight children have decreased slightly over the past ten years, the worrisome rate of wasted youngsters has not decreased. Children suffer more from malnutrition, and detecting it can assist lower the risk of mortality and physical or developmental problems by taking the required actions. In India, 20% of children suffer from wasting,48% of children suffer from stunting, and being underweight affects 43% which depicts the severity of this health issue that prevails all over the country. Using the machine learning technique to detect malnutrition assists in the healthcare sector. Categorizing malnutrition into their categories helps provide the treatment for that particular type of malnutrition that has been detected. When malnutrition in children is identified, it might be easier for individuals and healthcare professionals to take preventative action and lessen the negative effects on children. The research paper includes an innovative approach for detecting malnutrition using ensemble learning. We will evaluate the effectiveness of various transfer learning algorithms such as Inception-v3, VGG16 and VGG19, in detecting malnutrition in a patient dataset. Once malnutrition is detected, appropriate nutritional treatment can be provided to the patient. In this paper, various nutritional treatment recommendations are also explored. It takes input in the form of images and assigns weightage to various objects in images that help in differentiating kinds of malnutrition.

The main goal of this paper is to advance the development of more effective and trustworthy techniques for detecting and treating malnutrition through machine learning methods. The suggested approach has the potential to increase the precision and rapidity of malnutrition detection while also delivering individualized nutritional recommendations to patients, resulting in improved health outcomes.

2 Literature Review

The proposed model by Lakshminarayanan et al. used CNN to detect malnutrition in children. Alex Net architecture was used. Learning rate is 0.001 and accuracy is 96%. ReLU activation function was used to improve the rate of performance. Dataset included 500 images where 90% were used for training purposes and 10% for testing [1].

The proposed model by Kadam et al. summarizes a system that takes the image as an input and detects malnutrition using the TensorFlow algorithm in underage children. Here first of all the processing of the images is done, the features are extracted from the images which are used for disease analysis. The extracted features from the input images were then compared to those in the training dataset. With the help of this, one can conclude that the image color feature reasonably matched the training data [2].

Shetty et al. contributed to a system that used Agent Technology and Data mining technology. The techniques used were Multilayer-perceptron and Bayesian Networks but it resulted in inefficiency of the mall and the redundancy of the data because of the small size of the dataset [3].

Dhanamjayulu et al. aimed to detect individuals affected by malnutrition by analyzing facial images. The model utilized a combination of factors, including weight, age, gender, and BMI, to determine malnutrition status. To detect faces within the images, the researchers used a Multi-task Cascaded Convolutional Neural network. Additionally, a residual neural network was built and trained to estimate BMI values based on the facial images. The model seeks to establish a relationship between facial weight and appearance to estimate BMI values, ultimately enabling the identification of individuals affected by malnutrition. [4].

In their 2022 publication, Islam et al. proposed a model for detecting malnutrition among women in Bangladesh. The model employs five machine learning-based algorithms, namely decision tree, artificial neural network, Naïve Bayes, support vector machine, and random forest, to identify individuals who may be suffering from malnutrition. The model is designed to analyze various factors and indicators of malnutrition and provide accurate predictions based on the collected data [5]. From this paper it can be concluded that the Random Forest based classifier provides the accuracy of 81.4% for underweight women and for obese women it shows the accuracy of 82.4%. Combining MLR-RF based methods can more accurately detect malnourished women. The proposed approach aims to reduce the burden on healthcare services while also helping to identify women who are at a higher risk of malnutrition. By using machine learning algorithms to analyze various indicators of malnutrition, the model can accurately predict which individuals may require additional attention or support [5].

Talukder and Ahammed used five different machine learning algorithms to analyze data on children's health and nutrition. The algorithms used are Linear Discriminant Analysis, K-Nearest Neighbors, Support Vector Machine, Random Forest, and Logistic Regression. The model is designed to detect malnutrition in children aged 0-5 in Bangladesh. The goal is to identify malnourished children and provide them with the necessary treatment and support[6]. Out of which, it was concluded that Random Forest provided better accuracy as compared to other algorithms.

Najaflou and Rabieiindetected the malnutrition in the children of the age group of 6 - 12 years Decision Tree algorithm and AdaBoost Algorithm model was used for the recommendation system of the nutritional diet. The accuracy of the model was 90.27%. The dataset consisted of 1001 images out of which 806 were facing the problem of underweight. BMI was the main factor that was used in order to detect malnutrition[7].

Theilla et al. summarizes that Patients which are in intensive care units (ICU) are at greatest risk of malnutrition However, GLIM, a recognized diagnostic criterion for malnutrition, has not been authenticated for the patients in intensive care unit. SGA (Subjective Global Assessment) is an authenticated tool. Physician access to the nutritional status of inpatients is considered the gold standard [8].

Yin et al. developed the system of detecting malnutrition based on classification of tree-based machine learning models for cancer patients. The system included a dataset with 16 types of cancer. The GLIM criteria were used for the diagnosis purpose. A k test was performed to check the results obtained from the system and compare with the actual result. It helped in the pretreatment identification of malnutrition [9].

Browne et al. developed a system for the poverty and malnutrition prevalence based on the multivariate Random Forest. To improve the accuracy of the detection, a five-fold cross-validation approach was employed in conjunction with the use of two key parameters in the Random Forest algorithm: the maximum number of trees and the down-sampling rate for features. A sequence prediction framework was used for the better classification of the dataset [10].

Ahirwar et al.designed a system that utilizes several machine learning algorithms to predict the occurrence of malnutrition disease. In this paper, they use the WEKA tool to evaluate classifiers in a comparative manner in order to increase classification accuracy. The findings of this study on the malnutrition dataset demonstrate that linear regression processing effectiveness and prediction accuracy are superior to k-nearest neighbor, multilayer perceptron regression decision tree, and methods [11].

Kavya et al. created a novel machine learning-based application that can forecast the occurrence of malnutrition and anemia. This system is unique and can provide critical insights into the likelihood of these conditions. They employ technologies like "Visual Studio" for the front end and "SQL server" for the back end to construct the real-time application. They are both effective tools for using the real-time application. A team of researchers has created a system that describes various classification techniques that are applicable for identifying malnutrition and anemia in children who are younger than five years old [12].

Nyarko et al. developed a system using machine learning algorithms to predict undernutrition among children under five in Ethiopia. They collected data from the 2016 Ethiopian Demographic and Health Survey and used various machine learning models, with the xgbTree algorithm achieving the highest accuracy. The proposed system can facilitate earlier interventions and treatments to prevent undernutrition and its associated complications [13].

Wajgi and Wajgi have developed a system that uses machine learning to detect malnutrition in infants. They collected data on 550 infants and trained various machine learning models, with the random forest model achieving the highest accuracy of 92.6% in detecting malnutrition. The proposed system can facilitate earlier interventions and treatments to prevent malnutrition and associated complications [14].

3 Existing System

On the basis of numeric data, various algorithms were used to identify malnutrition in binary format (whether the person will have a deficiency or not). Malnutrition was identified based on age, height, and weight criteria. BMI was also the main factor that was used to detect malnutrition. To estimate BMI values, a residual neural network was created and trained. The association between body weight and facial features was predicted, as was the estimate of BMI using images of human faces [4]. With the help of images, the conventional neural network was used to detect and predict whether a child is affected by malnutrition or not. For classification purposes, Alexnet was used to identify patterns in images, as well as for recognizing faces and objects. The classification here is binary: whether or not a person will suffer from malnutrition or a nutritional deficiency [2]. The existing system is unable to classify all types of malnutrition into a single model. No additional research is done to determine how the disease will affect the individual. Malnutrition analysis is not provided because the treatment section is missing. Table [1] states the comparison between the existing and proposed system.

Table 1. Comparative table between existing and proposed system.

Approach	Advantages	Limitations
Physical Examination and Body Weight Measurement	Non-invasive and simple to execute.	This approach has limited capabilities to identify mild or moderate malnutrition and may produce inaccurate results in the presence of edema and dehydration. Additionally, it requires skilled professionals to perform the examination accurately.
Blood Tests	This technique offers detailed information on nutrient deficiencies in the body.	This method is invasive, costly, time-consuming, and necessitates specialized equipment and professionals.
Machine Learning Algorithms (Random Forests, Decision tree and Neural Networks)	Machine learning algorithms provide non-invasive, quick, and precise results. They can process large datasets and identify multiple factors contributing to malnutrition.	To provide accurate results, machine learning algorithms need a lot of high-quality data. The model may overfit the data, and its effectiveness

		depends on expertise in machine learning techniques.
Ensemble Learning (Combining Multiple Machine Learning Models)	Several machine learning models can be combined through ensemble learning to improve the reliability and accuracy of predictions. It can handle missing data and identify multiple factors contributing to malnutrition.	However, ensemble learning can be computationally expensive.
Proposed Approach (Ensemble Learning for Malnutrition Detection and Nutritional Treatment)	The proposed approach of using ensemble learning for malnutrition detection and nutritional treatment aims to improve the accuracy and speed of malnutrition detection. An ensemble learning system is developed that takes input images and classifies them into four categories: normal, wasting, stunting, and obesity. After detecting malnutrition, nutritional treatment is provided.	The proposed approach also requires a large amount of high-quality data and may be computationally expensive. It also requires expertise in machine learning techniques to be implemented effectively.

4 Methodology/Proposed System

The methodology of this proposed system for having deficiencies (Malnutrition) in people consists of three stages, first is the designing and training of the malnutrition detection model and second is the Recognition of Malnutrition type and further using the data of the person having that disease of Malnutrition will be useful for recommending the treatment and further suggest the future impact.

A. Malnutrition Type Classification

In this system, the design and test of a model for images have been done. The dataset includes various types of malnutrition deficiencies like Obesity, Stunting, Wasting, and normal where users can form the required words or sentences.
In this system, the implementation of ensemble learning with the use of a CNN algorithm and the use of transfer learning such as InceptionV3 and VGG16 has taken place. To train models, technologies used are TensorFlow and Keras. For implementation of the proposed system, it is further divided into five sub-groups that

include the collection of datasets of 4 different classes, the implementation of the model, the extraction and training of the datasets, the interfacing model with an application for recommending treatment and the impact of the type of malnutrition.
The first stage decides the base of the entire model and how it is to be implemented. The system starts with passing the image, then processing the input, and then passing it through the deep learning architecture. It is further explained in detail.

4.1. Collection and Classes of Datasets

For training the model, the dataset has been created. The dataset contains images that belong to 4 classes. These are Obesity, Stunting, Wasting, and normal. In table 2 it shows the four classes with its labels. Firstly, the dataset contains images that have been collected of different sizes. The neural networks get inputs of the images which are of the same size, they all need to be resized before inputting them to the CNN. Next, the dataset was split into separate training and testing sets. For training of models, the dataset is created with the help of data augmentation techniques using the augmenter library from the python module for increasing the images up to 4000. The images were too collected from different healthcare websites.

Table 2. Types with its labels

Labels	Malnutrition Type
0	Obesity
1	Normal
2	Stunting
3	Wasting

Fig. 1. Images from Dataset.

In Fig.1 it depicts the overview of the images that are present in the dataset.

4.2. Implementation of the Model

In the implementation of the model as given in fig.2 firstly it takes the input in the form of images. After preprocessing of images and resizing it to 224x224 size. It is passed through the deep learning architecture; it detects it in 4 different classes along with recommending a deficient person about treatment and its future impact by inputting the values of height and weight.

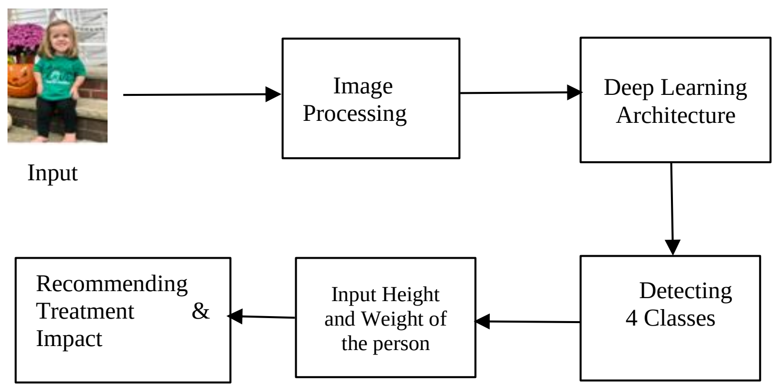

Fig. 2. Methodology of Malnutrition Detection System.

The project flow diagram is given.
In this diagram, the images in fig.3. are collected of 4 types and image processing is done i.e., remove the images which are of no use. So, after loading the dataset, generation of images is done using the python module known as augmenter, which produces about 4000 images. Prediction is done by applying different algorithms and one can input height and weight to know the recommendation, treatment and its impact.

Convolutional neural network (CNN) is used in image processing that is designed to process pixel data. After the images are passed through the system, the image is processed, and the datasets are loaded. A total of 3 convolutional, 3 Max Pooling, 1 flatten and 2 dense layers comprise the CNN [2].

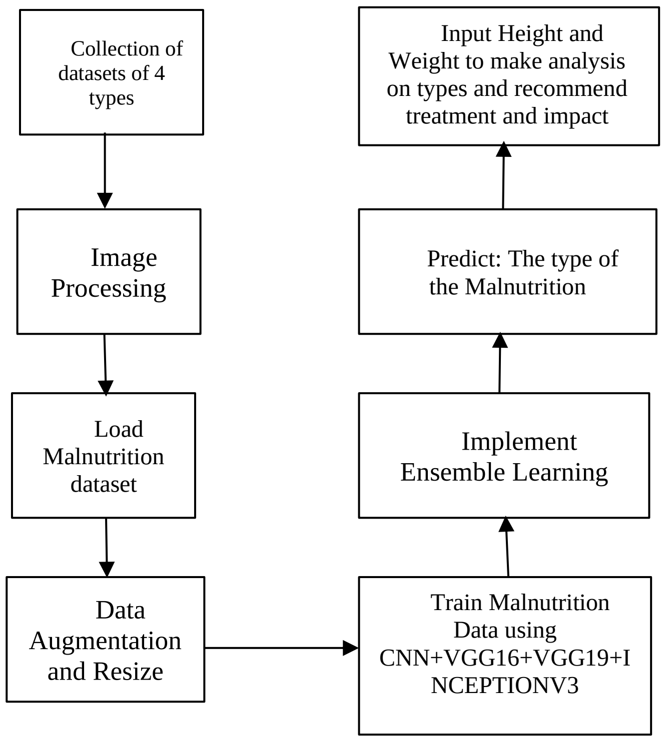

Fig.3. Flowchart for Detection of Types of Malnutrition

4.3. Transfer Learning-

The task is first learned using the pretrained network, after which the final layers are substituted with the new, smaller collection of pictures, allowing the classification to be applied to the new set of images. Transfer learning commonly expedites and simplifies network fine-tuning as compared to starting from zero and training a network with randomly initialized weights. Using the updated pre-trained network and the parameters, transfer learning is done at this step. The network is then trained to recognize the photos. In this case, the training images need to have a dimension of 224x224, thus a function is used to scale all of the images to this size [15].

Various models have been included from transfer learning are-

VGG16 model. As a 16-layer transfer learning architecture with only CNN as its foundation, VGG16 is relatively comparable to earlier architectures, however the configuration is a little different. For this architecture, the input image with a standard dimension of 224 x 224 x 3, where 3 stands for the RGB channel has been used [16].

Table 3. Summary of CNN classifier

Layer (type)	Output Shape	Param #
conv2d_3 (conv2D)	(None, 62, 62,16)	448
max_pooling2d_3 (MaxPooling2D)	(None, 31, 31,16)	0
dropout_4 (Dropout)	(None, 31, 31,16)	0
conv2d_4 (Conv2D)	(None, 29, 29,32)	4640
max_pooling2d_4 (MaxPooling2D)	(None, 14, 14,32)	0
dropout_5 (Dropout)	(None, 14, 14,32)	0
conv2d_5 (Conv2D)	(None, 12, 12,64)	18496
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6,64)	0
dropout_6 (Dropout)	(None, 6, 6,64)	0
flatten_1 (Flatten)	(None, 2304)	0
dense_2 (Dense)	(None, 128)	295040
dropout_7 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 4)	516
Total param: 319,140 Trainable params: 319,140 Non-Trainable params: 0		

InceptionV3. The Inception-v3 is a convolutional neural network that consists of 48 layers. The ImageNet database consists of pretrained network versions trained on over thousands of images. Several animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pre-trained network can classify photographs into. Therefore, the network contains extensive feature representations for various photographs. The input image for the network is 299 by 299 pixels in size [17].

1.3. VGG19 Model. A cutting-edge object-recognition model called VGG can accommodate up to 19 layers. VGG, which was designed as a deep CNN, performs better than baselines on several tasks and datasets outside of ImageNet. In comparison to VGG16, VGG19 has a few more convolutional relu units in the network's center [18].

Ensemble Learning. Ensemble learning is a method for solving specific computational intelligence problems by strategically generating and combining a number of models, such as classifiers or experts. The main goal of ensemble learning is to enhance classification, prediction, function approximation, etc. In this system 4 models were ensemble to make the accuracy of the model better [19].

4.4. Training and Testing of model

The main step after using different models is the ensemble learning to train the model. For training the CNN, transfer learning algorithms such as CNN, Inception-v3, VGG16 and VGG19 were combined together with the help of ensemble learning. The model is run on 50 epochs and saves the model. After training all the models the training and validation accuracy and their loss are given in table 4.

5 Results and Discussions

The proposed system used images of different types of malnutrition including in a folder such as obesity, wasting, stunting and normal. For training of models 80% of data is used whereas 20% is for testing. Dataset images are resized to 224 x 224 x 3 for training and testing purposes the taken images as input for classification. Following are the comparison between different CNN architecture with ensemble learning models.

Table 4. Comparison of accuracy of different algorithms

Sr. no.	Algorithms	Training accuracy	Validation Accuracy
1.	CNN	94.3%	57.14%.
2.	InceptionV3	92.3%	81%.

3.	VGG16	55.26%	35.29%.
4.	VGG19	88.5%	80.25%.
5.	Ensemble model	93%	84%.

Table 4 compares the performance of different algorithms based on their training and validation accuracy. The results show that VGG16 had the lowest accuracy with a training accuracy of 55.26% and a validation accuracy of 35.29%. The CNN model had the highest training accuracy of 94.3%, but its validation accuracy was only 57.14%. InceptionV3 and VGG19 performed better than VGG16 with training accuracies of 92.3% and 88.5%, respectively. However, the best performing model was the Ensemble model with a training accuracy of 93% and a validation accuracy of 84%.

Precision Recall and F1 score description-

Table 5. Comparison of Precision, Recall and F1 score of CNN algorithms

Classes	Precision	Recall	F1 score
Normal	0.43	0.87	0.57
Obesity	0.55	0.37	0.44
Stunting	0.67	0.63	0.65
Wasting	0.71	0.15	0.25

Table 5 displays the evaluation metrics for the CNN model, which were generated for four different types of classes. These evaluation metrics are used to assess the performance of the CNN model in classifying the different types of classes.

Table 6. Comparison of Precision, Recall and F1 score of ensemble model

Classes	Precision	Recall	F1 score
Normal	0.56	0.88	0.60
Obesity	0.70	0.55	0.54
Stunting	0.68	0.69	0.60
Wasting	0.80	0.59	0.39

Table 6 displays the precision, recall, and F1 score for the Ensemble model across different categories. These evaluation metrics are used to evaluate the performance of the Ensemble model in classifying instances from each category.

Prediction of images on test data-


```
1/1 [==============================] - 0s 67ms/step
stunting
The predicted image corresponds to "2"
```

Fig.4. Stunting Image Prediction

In fig 6., The model is inputted with an image and it predicts the image as a stunt.


```
1/1 [==============================] - 0s 206ms/step
obesity
The predicted image corresponds to "1"
```

Fig.5. Obesity Image Prediction

In this figure, the model is inputted with an image and it predicts the image as obesity.

Ensembled learning model gives good accuracy as compared with other architectures.

B. Analysis and impact on prediction of malnutrition deficiency

The analysis section included the categorization of the three types according to the height and weight provided by the user.
The dataset includes obesity wasting and normal categories based on the height and weight it classifies between different categories. It includes about 300 obesity data, 75 normal, and 35 wasting. The dataset was trained using a random forest algorithm. It includes 255 females and 245 males.

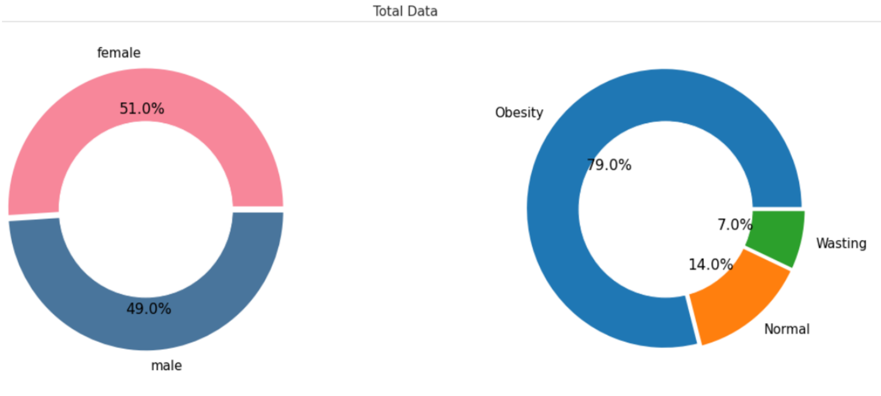

Fig.6. Pie chart of males, females and types of malnutrition types.

In fig.6. pie chart it shows the distribution of females and males according to data and how much of them are affected with the malnutrition type.
In fig.7. it shows number of trees vs accuracy. The number of trees depends on the number of rows present in the dataset, which are further combined to form the final decision of the model. It provides about 74% accuracy on the basis of values of height and weight using a random forest algorithm.
The impact section included the possibility of deficiency diseases of protein, vitamins, and minerals if the prediction is undernutrition and similarly for the obese it includes the possibility of hemosiderosis or hypervitaminosis as well as hypertension. Moreover, breathing problems can also be faced with difficulty in physical functioning. The treatment consists of replacing meals with low-calorie shakes or meal bars and eating more plant-based foods and getting at least 150 minutes of physical activity to prevent further weight gain. The impact of wasting includes feeling tired as well as weaker and depressed. The treatment includes adding ready-to-use therapeutic food to the diet The impact of the stunning is a frequent illness as well as recurrent

undernutrition. It prevents the children from reaching their physical and cognitive strengths.

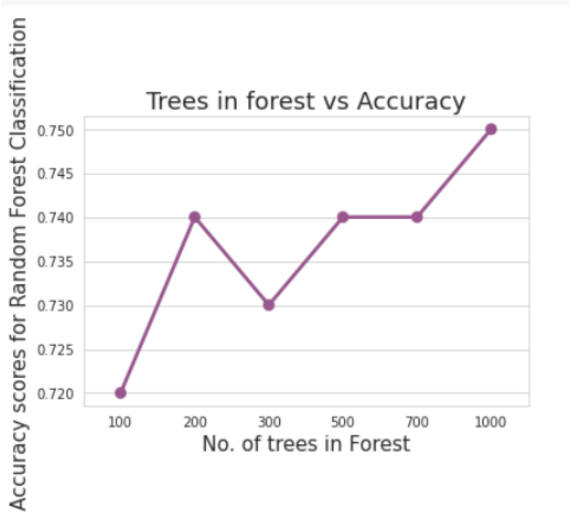

Fig. 7. Graph of Trees in forest vs Accuracy

The treatment includes giving vitamin A with zinc and plant-sourced foods in the diet. Furthermore, an exact nutritional diet chart can be obtained from the doctor to seek medical advice.

6 Conclusion

Malnutrition is incredibly prevalent and has impacted numerous nations worldwide in one or more ways. Malnutrition detection or prediction will assist the government or health services in implementing preventative measures. Types of malnutrition are found using the convolutional neural network (CNN or ConvNet) technique. Normal and deficient people's pictures are the input. InceptionV3, VGG16, and VGG19 is a CNN architecture that does classification tasks and looks for patterns in photos to identify faces and objects. The system predicts whether or not a person would suffer from which type of malnutrition utilizing parametric settings. Ensemble learning is used to take the average of the 3 CNN architecture algorithms used. Additionally, it does an analysis of predicted output and provides proper treatment and impact to the person. The system can provide the doctor assistance for the proper guidance of the medical treatment. Furthermore, it can also add the diet tracker option which will track their daily consumption and notify them. The lab test facility can be made available for them via which they can test and come to know about more precision value of the different vitamins.

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