Measles Rash Disease Classification Based on Various CNN Classifiers

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Abstract. One of the most thoroughly researched and well-documented non-linear infectious disease dynamical systems is measles. Infants and young children are most likely to contract the immunizable disease measles. Measles is a highly commutable viral infection that has a 90% secondary infection incidence among contacts who are vulnerable. In this study, we have used a deep convolutional neural network to discriminate between various skin diseases and measles rash. The categorization performance of each individually optimized DL model across all of their ensembles has been presented using the specified dataset. We tested four optimizers, namely SGD, ADAM, RMSprop, and RAdam, on three considered models in order to further improve them. These models include VGG16, InceptionV3, and ResNeXt50, on which individual 10-fold cross-validation is done. The maximum average 10-fold cross-validation accuracy of 98.62%, 99.31% recall, and 99.32% F1 score were achieved by the optimised Inception V3 using the SGD optimizer. Finally, our predictive model offers a method for early detection to assist physicians in treating and enforcing new laws and regulations.

Keywords: Convolutional Neural Network · Measles · InceptionV3 · SGD

1 Introduction

Measles also called rubeola is a highly contagious respiratory infection caused by a virus named morbillivirus belonging to the paramyxovirus family [1]. Measles outbreaks can lead to epidemics that result in numerous fatalities. It is an airborne disease that readily transmits from one individual to another through many ways including coughs, sneezes, and direct contact with the mouth or nasal secretions of an infected person. Measles is a highly contagious disease where nine out of ten people who are not immune and are nearby an infected individual will be affected. Symptoms can be usually observed within 14 days of exposure to the virus. Once a person gets exposed to the virus then within the next 10 days to 14 days it usually results in a high fever, runny nose with red and watery eyes, and results in white spots developing inside the cheeks at the starting stage. Later once the virus develops and expands then slowly rashes erupt, firstly a red rash begins as flat red spots on the face which then spreads down the body, after

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that small, popped bumps and raised white spots appear on top of flat red spots of the red rash. Rashes will only last for 5–7 days and eventually reduces. The rashes often appear 14 days after being exposed to the virus. General symptoms of measles include high fever, cough, runny nose, tiredness, inflamed eyes, white spots in the mouth, sore throat, sensitivity to light, muscle pain, and a red rash. Severe complications observed could include encephalitis, dehydration, blindness, severe diarrhea, severe respiratory infections like pneumonia and ear infections. Early and late-stage central nervous system (CNS) consequences following acute measles are significant and frequently deadly [11]. Due to their vulnerability to several illnesses and vitamin A deficiency, young children who are malnourished and have weak immune systems are more susceptible to developing severe measles. Children below the age of five and adults above the age of 30 have a higher risk of complications. Measles is most observed in Infants and children especially malnourished children and so is often believed to be the common age group affected by measles hence measles is often regarded as a childhood illness, even though measles is typically thought of as a childhood illness, it can infect anyone at any age [7]. Prior to the development of measles vaccines, 95%–98% of children by the age of 18 were infected with the virus [8].

A wide range of clinical signs, from a typical mild self-limiting infection to mortality, are seen in measles patients. Measles is still common in many underdeveloped countries, particularly in parts of Asia and Africa. Measles may be eradicated from a population; however, this needs coverage with two doses of vaccination at rates ranging from 93% to 95% of the population [9]. Nearly 95% of measles deaths occur in countries with poor healthcare infrastructure and low per capita income levels. Measles can infect anyone who hasn't received a vaccination. Nearly everyone contracted the disease before the development of the measles vaccination. Measles, which was assumed to be a vanishing viral infection due to vaccination, has resurfaced globally. This has been linked to anti-vaccination campaigns in the early twenty-first century [2]. The measles vaccine is administered frequently in conjunction with other immunizations and has been proven to be safe and effective at avoiding the disease. Between 2000 and 2017, measles mortality decreased by 80% as a result of vaccination, and as of 2017, 85% of kids globally have received their first dose. Measles affects around 20 million people each year, primarily in underdeveloped countries in Africa and Asia. Measles killed 2.6 million people in 1980 and 545,000 in 1990; by 2014, global immunization initiatives had reduced measles deaths to 73,000. Despite these trends, sickness and death rates have rapidly increased from 2017 to 2019 due to a decline in immunization.

Accurate virus diagnosis will be essential in reducing the number of illnesses as the virus spreads throughout the world. Because of how contagious measles is, outbreaks are a sign that the healthcare system needs help [3]. However, because the disease is less widespread than many others, it is more challenging to identify the virus, particularly for young medical professionals with minimal expertise. Since the other symptoms of measles are mostly interchangeable with those of other illnesses, the skin rash that it causes is its most distinctive characteristic. Healthcare professionals utilize the rash's particular pattern and its distribution over the body to visually diagnose the illness. Across many disciplines, including medicine Artificial intelligence-based classification models have significantly changed how predictive decision-making is done [18]. Deep learning technologies, with their capacity to automatically learn semantic features from big datasets, are becoming useful in the detection of diseases [17]. In this study, we apply convolutional neural networks, a type of neural network model, to identify the measles rash using an image dataset by extracting higher representations of the visual information. We deploy a variety of CNN models, including VGG16, Inception V3, and ResNeXt50, along with optimizing techniques including SGD, ADAM, RMSprop, and Adam to help detect measles virus infection. The rest of the paper is structured as follows: Sect. 2 addresses related work, Sect. 3 talks about data, Sect. 4 discusses the methodology, Sect. 5 describes the results, and Sect. 6 concludes the paper.

2 Related Work

Convolutional neural networks (CNNs) have achieved near or even superior performance than humans in the imaging sector [14]. Li, Ling-Fang, et al. findings show that deep learning-based skin disease image identification beats dermatologists and other computer-aided treatment approaches in skin disease diagnosis, with the multi-deep learning model fusion method having the maximum recognition effect [13]. Income level and Measles cases have a link. Geographic Information System (GIS) can help in disease prevention decision-making, such as in the case of measles [5]. Glock, Kimberly, et al. made use of transfer learning to construct Deep CNN to differentiate measles rash from various skin diseases. Analysis with the Residual Neural Network −50, which was trained on a varied and regulated array of skin rash images, produced 95.2% classification accuracy, 81.7% sensitivity, and 97.1% specificity. This shows that the strategy is effective in assisting with the detection of measles to aid in the containment of outbreaks [6]. Wu, Z. H. E., et al. discovered that transfer learning models have higher average precision and recall [14]. Several deep CNN architectures are proposed to investigate the potential of Deep Learning trained on the "DermNet" dataset for the diagnosis of 23 different types of skin diseases. These architectures are compared to determine which one performs the best. The method demonstrates that DenseNet was the most accurate for skin disease classification using the DermNet Dataset, with a Top-1 accuracy of 68.97% and a Top-5 accuracy of 89.05% [10]. To diagnose three skin illnesses, the classification performances of five deep network architectures were investigated. Comparisons were made using the accuracy, specificity, precision, F1 metric, and MCC. According to quantitative results, ResNet101 can classify images more accurately than the other networks [15]. According to the experimental findings of the classification of Pneumonia using Inception-V3 and Convolutional Neural Networks from X-Ray Images by Mujahid, Muhammad, et al., Inception-V3 with CNN achieved the highest accuracy and recall scores, at 99.29% and 99.73%, respectively [16].

Ali, Shams Nafisa, and colleagues demonstrated how to extract picture features using a convolution neural network and the deep learning idea. To classify monkeypox and other diseases, multiple pre-trained deep-learning models, including VGG-16, ResNet50, and InceptionV3 are used. A combination of the three models is also created. ResNet50 achieves the highest overall accuracy of 82.96 (4.57%), while VGG16 and the ensemble system achieve 81.48 (6.77%) and 79.26 (1.05%), respectively. As an online monkeypox screening tool, a prototype web application is currently being created [12].

There is a need to precisely identify measles rash from the images of the various skin diseases and provide the required treatment on time to reduce the complications and death rate. Improving the ability to identify measles would benefit healthcare professionals in tackling the impending measles problem and the prospect of measles returning to the country, the dermatologists are in scarce supply in many areas and hence deep learning and image classification concepts can improve public health in many poor nations. Deep learning-based convolutional neural network models prove to have a good potential in detecting various skin diseases and have been effectively used by various researchers; improvising on the above, we propose to use three different convolutional neural network models, namely VGG-16, ResNeXt-50, and Inception V3, with four different optimizers, namely SGD, ADAM, RMSprop, and Adam, on which we implement a 10-fold cross-validation for better predictions.

3 Data

An image dataset of various skin conditions and rashes was downloaded from IEEE-Data Port. The dataset contains images of rashes of 11 different diseases. The dataset also contains pictures of people without any skin infections. There are two folders called "Train" and "Test" under the directory "images". In the "Train" folder, there are two sub-folders named "Measles" and "Not Measles", each containing 126 and 926 images respectively. In the "Test" folder, there are two sub-folders named "Measles" and "Not Measles", each containing 32 and 232 images respectively. It has images containing 11 different rashes and normal skin. A detailed description of the dataset is represented in the table below Table 1.

Table 1. Information about our dataset

Image Class	# of images
Chickenpox	170
Measles	158
Ringworm	131
Bowen's Disease	124
Psoriasis	122
Enterovirus	117
Keratosis	112
Eczema	95
Chigger Bites	87
Dermatofibroma	80
Scabies	79
Normal Skin	41
Total	1316

The following pictures displays two illustrations of our dataset, Fig. 1 shows Measles rash and Fig. 2 shows Chickenpox rash. The similarity in appearance of the two types of rashes represents a challenge in differentiating the measles rash from other skin problems.

Fig. 1. Measles Rash

Fig. 2. ChickenPox Rash

4 Methodology

4.1 Model

Convolutional Neural Network is an artificial deep learning neural network model applied to analyse visual imagery. The CNN architecture has demonstrated outstanding performance in a wide range of Computer Vision and Machine Learning challenges [4]. Different layers in CNN are the Convolution layer, Pooling layer, ReLU layer, and fully connected layer. In this study, we have implemented 3 different types of CNN Architectures namely VGG16, Inception V3, and ResneXt50, and applied SGD, ADAM, RMSprop, and Adam optimizers which are used to reduce the overall loss and improve the accuracy.

4.1.1 VGG-16

The VGG model stands for the Visual Geometry Group from Oxford. An illustration of VGG-16 model is shown in Fig. 3. This model is far more in-depth than AlexNet and it is quite intuitive. A convolutional neural network with 16 deep layers is called VGG-16. Its image input dimensions are 224 by 224. In the considered dataset there are two distinct folders—train and test folders—have been created for the pictures. The train and test folders are split so that 80% of the data's photos are utilized for training and 20% are used for testing. To execute 10-fold cross-validation, all libraries were installed from Keras. The input size and weights of the image with type = 32 were used to build the VGG model. Therefore, a package called glob is used to mount the folders from the training sample from the drive to train the model. The model includes three layers. In Layer 1, there are two CONV 2D layers and a MaxPooling layer. In Layer 2, there are two CONV 2D layers and a Pooling layer, and in Layer 3, there are three CONV 2D layers and a Max, with the other two layers having the same format and being followed by a dense layer.

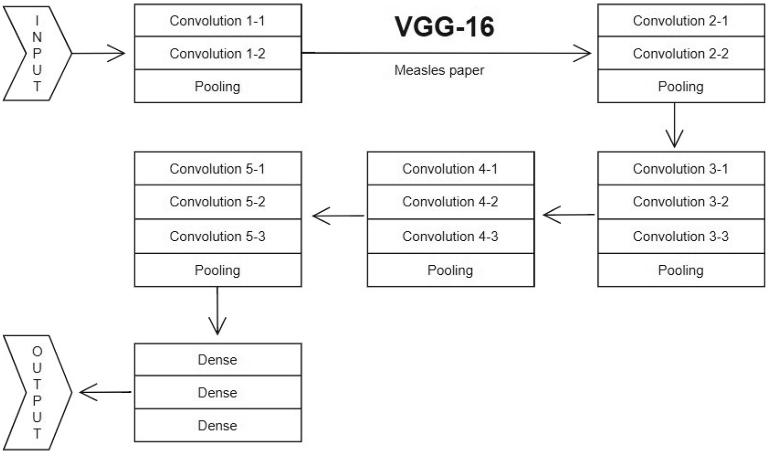

Fig. 3. Illustration Of VGG-16 Model

There are 14,764,866 parameters altogether. 50,178 are the trainable parameters, and 14,714,688 are the non-trainable parameters. After the model has been run, the model.h5 file is created automatically. Next, using the Keras Image Data Generator with the parameter's width shift range argument = 0.2, rotation range argument = 40 and height shift range argument = 0.2, train and test sets have been created. In the train set, we discovered 1050 images that belonged to two classes, while in the test set, we discovered 264 images that belonged to two classes. Model.h5 has now been utilized to assess the model and determine all potential metrics by building a confusion matrix.

4.1.2 ResNeXt50

ResNeXt replaces the residual block with a "split-transform-merge" strategy, which is similar to Inception's module but differs in the aspect that Inception employs a separate filter and size for each block, ResNeXt uses shared hyper-parameters. It also uses a much more parallel stacking layer than sequential layers. ResNeXt is named the ILSVRC 2016 classification task's first Runner Up. The learning ratio is low when compared to AlexNet and VGG because those architectures do not provide batch normalization. This model corresponds to a single node with 8 GPUs, learning ratio of 0.1 and batch size = 32. The libraries are used to assess the model image classification. To train the model, batch normalization is performed on the input, then a 1x1 convolution layer is added, followed by max pooling, then a four-stage layer of grouped convolution, global average pooling, residual connection, and max pooling to create a fully connected layer. On the whole, in_features are 2048 and out_features are 1000 where bias is True. An illustration of ResNeXt50 model is shown in Fig. 4.

4.1.3 Inception V3

For image classification, Inception V3 is performed which is a simplified version of Google Neural Network where it is employed. This type employs several filters of various

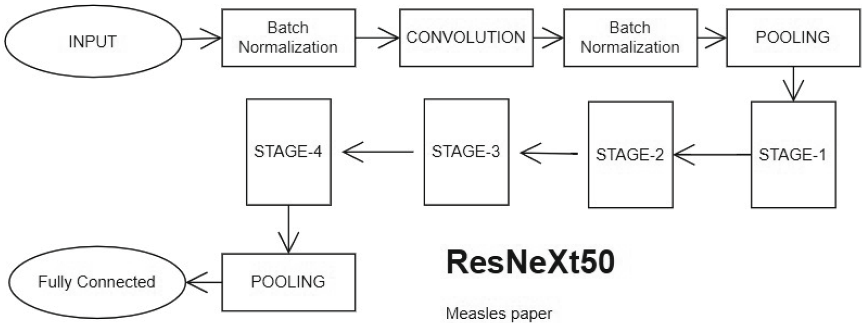

Fig. 4. Figure Of The ResNeXt50 Model

sizes. Inception V3 is a better model adaptation since it utilizes regularizers with higher efficiency and uncompromised speed. Among other advancements, the Inception-v3 convolutional neural network architecture makes use of Label Smoothing, factorized 7 $\times$ 7 convolutions, and the addition of an auxiliary classifier to move label information lower down the network. The Inception V3 model has 42 layers in total, which is slightly more than the inception V1 and V2 models. Traditionally, the grid size of the feature maps was decreased using maximum and average pooling. The activation dimension of the network filters is enhanced in the Inception V3 model to decrease the grid size more. In comparison to its competitors, Inception V3 may attain the lowest error rates.

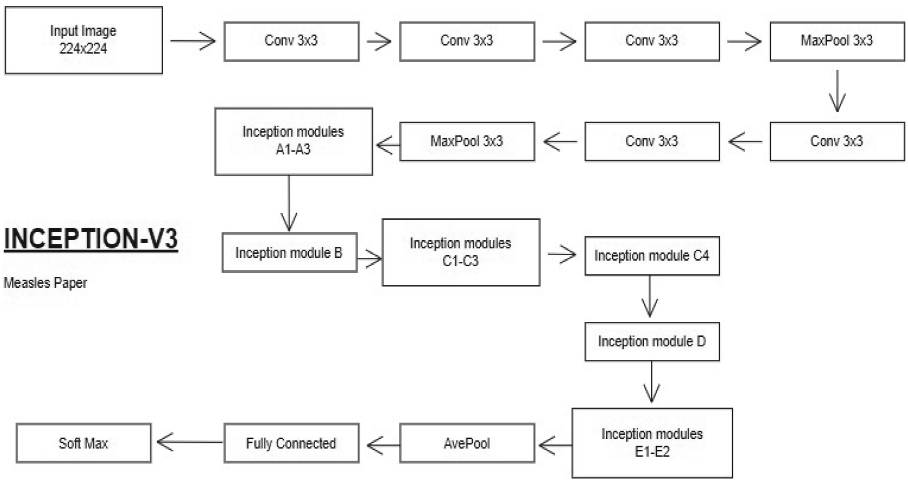

Fig. 5. Inception V3 architecture

By examining Fig. 5, we can comprehend the Inception V3 architecture. After Concatenate in the Inception V3 model, it flows through Dense, Dropout, and ultimately Dense Soft Max Layer.

4.2 Optimizers

In Deep Learning Neural Networks, optimizers are used to change model's parameters. An optimizer's job is to reduce model weights to minimize a loss function. The loss function is used to analyse the model's performance. A neural network model must be trained using an optimizer. The algorithm's foundation is randomness, which is mentioned as stochastic. Rather than using the entire dataset for each iteration in stochastic gradient descent (SGD), we elect the data batches at random. This suggests that we only sample a small portion of the dataset.

Adam may be a different optimization algorithm that can be used to train deep learning models instead of stochastic gradient descent. Adam creates an optimization technique which will handle sparse gradients in noisy situations by combining the best features of the AdaGrad and RMSProp algorithms. Root Mean Squared Propagation, or RMSProp, may be a variation on gradient descent, and therefore the AdaGrad version of gradient descent adapts the step size for each parameter using a declining average of partial gradients. Rectified Adam, often known as Adam, is a stochastic optimizer variation that adds a term to correct the adaptive learning rate's variance. It attempts to solve Adam's terrible convergence issue.

The three CNN models considered have been trained using four optimizers (i.e., ADAM, RSMprop, SGD, RAdam). The higher accuracy of the 10-fold cross-validation and testing data is served as basis for separation between these 12 variations. A few further tests were performed on the most accurate model to evaluate how it performed under various conditions.

5 Results and Discussion

We may infer from Table 2 that, among all the models with optimizers applied to them, the Inception V3 model with the SGD optimizer has the best average 10-fold cross-validation Accuracy (98.62%). The average 10-fold cross-validation accuracy is less than 90%, for ResNeXt50 with SGD optimizer. VGG16 model with Adam optimizer achieves the second highest average 10-fold cross-validation accuracy. The RAdam optimizer achieves the highest average 10-fold cross-validation accuracy of 97.9% in the ResNeXt50 model.

Table 2. Results using four optimizers for VGG16, InceptionV3 and ResNeXt50.

Model	Optimizer	Average 10-Fold Cross Validation Accuracy (%)
VGG16	SGD	96.91
	ADAM	98.59
	RMSprop	97.40
	RAdam	98.50
Inception V3	SGD	98.62
	ADAM	96.95
	RMSprop	97.77
	RAdam	96.43
ResNeXt50	SGD	89.35
	ADAM	97.48
	RMSprop	97.68
	RAdam	97.90

Precision is a metric used to analyse a model's dependability and its accuracy in categorizing a sample as positive. It is calculated using the ratio of True Positives to True Positives and False Positives.

$$Precision = \frac{True_{positive}}{True_{positive} + False_{positive}} \tag{1}$$

The Recall parameter is used to assess how well the model can identify positive test data. It is determined by the ratio of Positive samples that were correctly labelled as positive to the total number of positive Instances samples. The greater the Recall value, the greater the number of positive samples detected.

$$Recall = \frac{True_{positive}}{True_{positive} + False_{Negative}} \tag{2}$$

Models for classification include the F1 Score. The F1 Score is focused on precision and recall. The Harmonic mean of Precision and Recall is the F1 Score.

$$F1Score = 2 * \frac{Precision * Recall}{Precision * Recall} \tag{3}$$

Table 3. Precision, Recall, F1-score of the considered models with optimizers

Model	Optimizer	Precision (%)	Recall (%)	F1-score (%)
VGG16	SGD	97.92	98.08	97.99
	ADAM	99.34	99.31	99.32
	RMSprop	98.62	99.67	99.14
	RAdam	98.8	99.34	99.07
Inception V3	SGD	99.34	99.31	99.32
	ADAM	96.83	96.44	96.63
	RMSprop	99.54	96.53	95.01
	RAdam	99.01	98.71	98.25
ResNeXt50	SGD	96.49	96.39	96.43
	ADAM	99.18	99.15	99.16
	RMSprop	99.34	99.31	99.32
	RAdam	99.14	99.08	99.11

From Table 3 we can observe the highest Precision of 99.54% was obtained for Inception V3 with RMSprop as optimizer. The highest Recall of 99.67% has been observed for VGG16 with RMSprop as optimizer. VGG16 with ADAM optimizer, Inception V3 with SGD optimizer, and ResNeXt50 with RMSprop optimizer have the highest F1 Scores, each recording 99.32%.

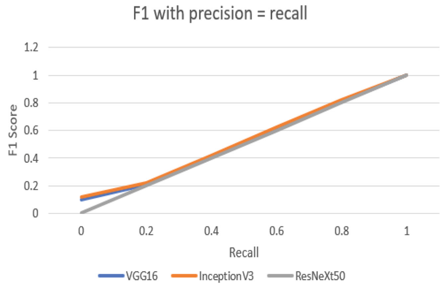

Fig. 6. F1-Score Recall Curve

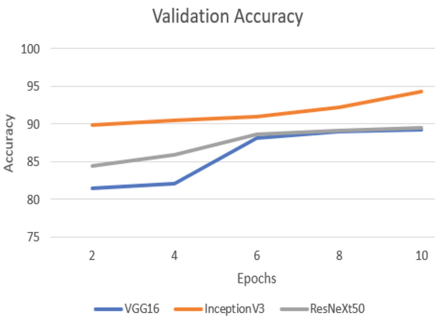

Fig. 7. Accuracy Values Versus Epochs

We have plotted Recall against F1-Score in Fig. 6. The Validation Accuracy increases as the number of Epochs increases as observed in Fig. 7.

The most popular cost function is called Cross Entropy Loss. It is used to reduce the loss. The output of cross-entropy loss, also known as log loss, which produces probability value between 0 and 1, is used to assess the effectiveness of classification models.

$$-(ylog(p) + (1 - y)log(1 - p)) \tag{4}$$

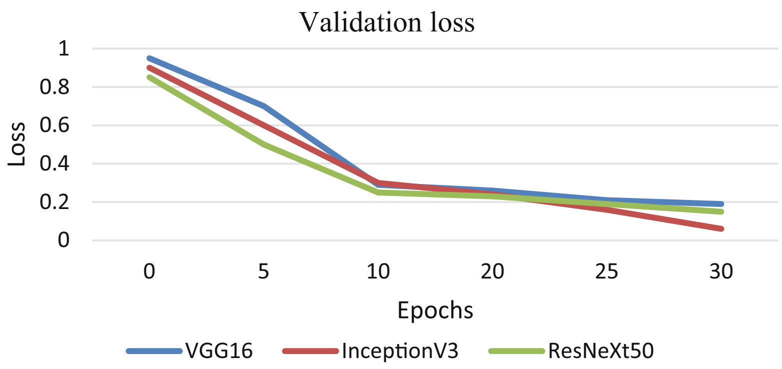

Fig. 8. Loss function values plotted against the Number of Epochs

As validation loss increases, we usually observe overfitting. In order to reduce overfitting, we use cross-entropy loss function Fig. 8. Depicts that as the number of Epoch increases then validation initially decreases, at a particular point it remains constant and then decreases again.

Fig. 9. Plots on application of various optimizers on considered CNN models

From Fig. 9 we can see that by utilizing any of the following optimizers SGD, RMSprop, ADAM and RAdam; InceptionV3 has obtained the highest average 10-fold cross-validation accuracy.

6 Conclusions

Most measles cases range from mild to quite severe. But measles can also cause encephalitis, pneumonia, and even fatalities. Because the measles rash gradually spreads to the hands and feet, a skilled model is needed to identify the rash and take the appropriate safety measures to avoid fatality. We conducted research utilizing three different deep neural network architectures (VGG16, InceptionV3, and ResNeXt50) and four different optimizers (ADAM, RAdam, RMSprop, and SGD) to distinguish between images of the measles and those that were not. Inception V3 with SGD optimizer displayed the highest average 10-fold cross-validation accuracy of 98.62% with 99.31% Recall and 99.32% F1 Score among the 12 model versions we looked at as well as the results are listed in Tables 2 and 3.

In the future, we will use autoencoders because Convolutional Neural Networks needs a huge sample data for training the model, but we only have a restricted number of photos. We learn about low-dimensional data representations with their help by selecting relevant characteristics with little adjustment and relying on confidence intervals rather than point estimations. For our CNN model to be more effective in diagnosing human skin diseases, it could also be required to expand our dataset to detect a wider range of rash disorders. We intend to investigate further optimizers in the future to enhance system performance even more. Additionally, we want to create a web application that will let users submit photos captured with their cameras or from libraries of images. The Inception V3 model examines supplied images to determine whether they are measles-positive or negative. If positive, a message such as “MEASLES DETECTED, PLEASE SEEK MEDICAL ATTENTION IMMEDIATELY” is displayed along with the model accuracy.

By creating a web application which can be utilized as a dynamic tool to treat measles disease as the frequency of the disease grows, doctors can take advantage of the advancement of technology.

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