Assessment of Nail Images for Preliminary disease detection and classification based on CNN: The New Horizon in Disease Detection in Humans.

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Abstract. Digital image processing has wide scope in globe such as military, medical, robotics, forensic science etc. Now a day for such type of applications feature extraction of digital image is important part of processing. Pattern recognition requires the classification of medical imagery. Classification improves the efficiency and accuracy. For the classification process, image preprocessing, fragmentation, and feature extraction might be used. Preliminary disease detection rate depends on all the steps but classification has its own importance in pattern recognition. A CNN model for preliminary disease prediction and categorization in humans is presented in this research. The collection includes 750 photos of nails with four disease signs. To automate feature extraction and categorization, we used a CNN model. In the early phases of disease prediction, colour information is routinely used. In our concept, the filters are applied to three channels depending on RGB components. According to tests, the proposed method accurately predicts diseases.

Keywords: Digital image processing, InceptionV3, Nail features Analysis, InceptionResNetV2, disease prediction, MobileNetV2, Convolutional Neural Network (CNN), EfficientNetB0.

1. Introduction

Number of diseases can be easily determined by observing nails of both hand and leg. In medical research and technology, digital image processing is a crucial topic. In the modern era majority of doctors uses digital technology to diagnose the diseases. Image analysis techniques will be used for a variety of objectives, including detecting diseased areas of certain organs, locating and quantifying disease-infected areas, and identifying the colour, size, and shape of infected areas in order to diagnose the disease. The basic processes for the image processing technique to address the problem are picture acquisition, image analysis, fragmentation, feature extraction, database comparison, and result. Various diseases affect the appearance of nail by colour, texture, shape and pliability. Automatic disease prediction from raw photos is now achievable because to advances in artificial intelligence research. Deep learning is a learning approach based on neural networks. One of the benefits of deep learning is that it can automatically extract features from photos. The neural network learns how to extract features during training. The common model of deep learning is CNN, which is a multi-layer feed-forward neural network. In recent years, CNN models have been widely used in picture classification difficulties. Lee at al. [3] propose an integrated model that uses CNN and

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Deconvolutional Networks to extract contextual information from leaf features (DN). Konstantinos at al. [4] on a massive data collection of open leaves; we ran many pre-trained CNN models. Their research shows that CNN is an excellent tool for detecting plant diseases automatically. Durmus at al. [5] AlexNet and Squeeze pre-trained CNN models were applied to tomato leaves from an open dataset to detect diseases. Atabay at al. [6] We fine-tuned a pre-trained model and constructed a new CNN model to diagnose tomato leaf disease. A customised CNN model outperforms a pre-trained model, according to their findings. Setting up a suitable CNN model that produces higher accuracy values is tricky. Zhang at al. [7] Researchers introduced a three-channel CNN model based on RGB colours to detect vegetable leaf diseases. Because plant leaf images are complicated with their backgrounds, the colour information acquired from a single colour component is restricted. As a result of this, the accuracy of the feature extraction method suffers. Using a variety of colour components rather than a single one is more promising. On the Plant Village dataset, In the proposed work, we constructed a CNN model based on RGB components of tomato leaf images [8]. We chose the Learning Vector Quantization (LVQ) algorithm as a classifier because of its topology and dynamic model. Mohanty et al. (2016) [16] uses both AlexNet , GoogleNet models and achieves 99.27% in AlexNet and 99.34% in GoogleNet. With 80.6 % on images and on video 70.4 % accuracy, Ramacharan et al. (2019) [17] Use the Single-shot multibox (SSD) model in conjunction with the MobileNet detector and classifier. With 96.46 %, Geetharamani et al. (2019) [18] uses a deep CNN model with nine-layer. Chen et al. (2020) [19] implements a 92 % accurate INC VGGN model. SVM and RF model with Shallow CNN for 94 %, Li et al. (2020) [20]. Deep residual neural network (DRNN) model with 96.75 % by Oyewola et al. (2021) [21].

The following is the order in which the paper is organized: Section I represents introduction. Section II represents information about CNN. The LVQ algorithm is described in Section III. The proposed method for detecting and classifying diseases is presented in Section IV. Section V assesses the outcomes of the experiments. Finally, section VI brings the paper to a close.

2. Convolutional Neural Network

Deep learning is a term used to describe a collection of machine learning approaches that include several layers. Each layer receives the output of the preceding layer as input. Unsupervised, supervised, or semi-supervised learning are almost all methods. Deep learning is defined by LeCun et al. as a portrayal learning method [9]. Representation learning techniques use optimizations to find the most convenient way to represent data [5]. Deep learning does not require feature extraction and classification to be separated because the model extracts the features automatically as it is trained. Image processing, image restoration, natural language processing, speech recognition, and bioinformatics are just a few of the applications. CNN is used as a deep learning method in this investigation. CNN is successful in assessing visual images and can easily separate the required features because to its multi-layered structure. It can recognize and classify items quickly and with little pre-processing. The convolutional layer, pooling layer, activation function layer, and fully connected layer are the four basic layers. A generic CNN architecture is shown in Figure 1.

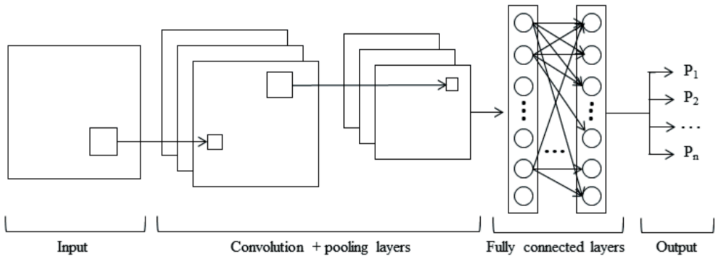


Fig. 1 Common CNN architecture.

2.1 Convolutional Layer

The convolution layer is the source of CNN's nomenclature. The map of the features of input image is extracted using a series of mathematical procedures in this layer [10]. A filter is used to minimize the dimensions of the input image. The filter is gradually relocated from the upper left corner of the image. At each stage, the image's values are multiplied by the filter's values, and the outcome is added together. A new matrix with a smaller size is created using the supplied image.

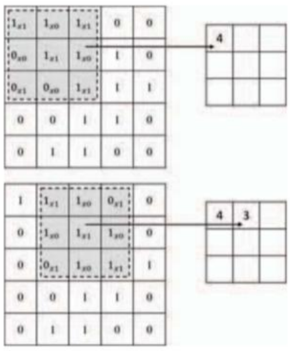


Fig. 2. Convolution for a 5x5 input image with a 3x3 filter

2.2 Pooling Layer

The pooling layer is typically used after the convolution layer. The output matrix obtained from the convolution layer is reduced by this layer. Although alternative filter sizes can be used in the pooling layer, 2x2 is the most typical. Functions like max pooling, average pooling, and L2-norm pooling can be implemented in this layer. In this study, the max pooling filter with stride 2 was applied. The biggest value in each of the sub-windows is selected and transferred to a new matrix to achieve max pooling. Figure 3 depicts an example of pooling.

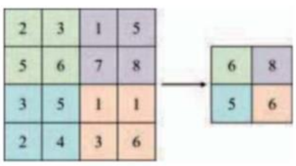


Fig. 3 Pooling Process

2.3 Activation Layer

In artificial neural networks, the activation function forms a curvilinear relationship between the input and output layers. It affects the network's performance. Non-linear network learning is accomplished using the activation function. Alternative activation functions include linear, sigmoid, and hyperbolic tangent, however CNN most commonly uses the nonlinear ReLU (Rectified Linear Unit) activation function. Values less than zero are set to zero in ReLU, whereas values greater than zero remain unchanged (1).

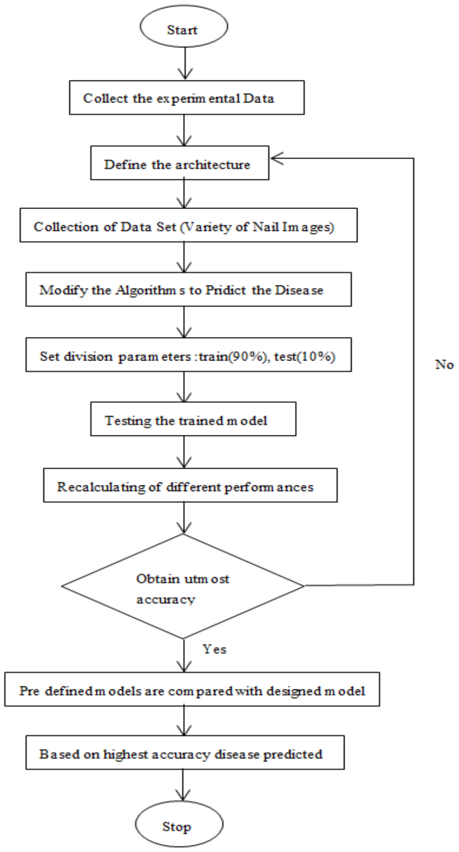
$$f(x) = \begin{cases} 0, & \text{if } x < 0. \\ x, & \text{otherwise.} \end{cases} \qquad (1)$$

2.4 Fully Connected Layer

The final formed matrix is provided as input into the fully linked layer once the convolution, pooling, and activation procedures are completed. This layer is in charge of categorization and recognition.

3. Experimental Work

Standard CNN models are more expensive to compute since they have a high number of features. We replaced normal convolution with level of detail convolution in this research, which minimize the number of variables and computation time. The models that were put into place had been trained using an available dataset that included 4 categorical illness classes. Various criteria such as batch size, dispersion, and the number of epochs were used to assess the models' performance. Using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, the implemented models achieved disease-classification accuracy rates of 98.42 %, 99.11 %, 97.02 %, and 99.56 %, respectively, which were greater than standard techniques. Nail image datasets in RGB format were employed in our experiment. We started with coloured nail images and then moved on to resize images from the same dataset. By 90 % for training purposes and 10% for testing purposes, all nail images were divided into two sets, a training set and a testing set. Following is the flowchart of methodology used.



The implemented CNN architectures uses parameters (values) wise as Training epoch (30–50), Batch size
(32–180), Dropout (0.2–0.8) and Learning rate (0.01–0.0001).

4. Result

The accuracy of all models with loss and number of epochs are for InceptionV3 model with accuracy 98.92% with loss 0.0392 and 50 epoch. InceptionResNetV2 model with accuracy 99.47% with loss 0.0731 and 50 epoch. MobileNetV2 model with accuracy 97.17 % with loss 0.0921 and 50 epoch. EfficientNetB0 model with accuracy 99.75% with loss 0.0137 and 50 epoch.

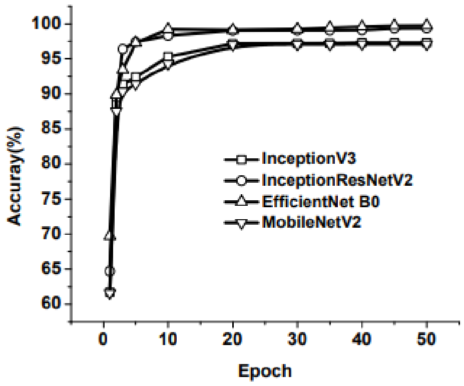


Fig. 4. The implemented model's accuracy in terms of performance.

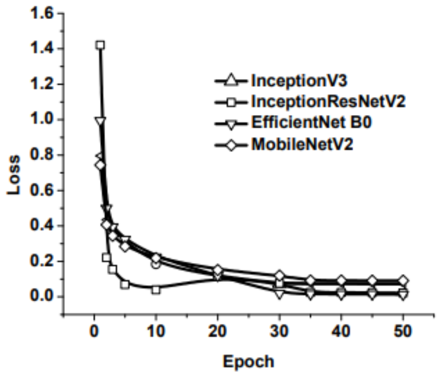


Fig. 5. Performance loss of implemented model.

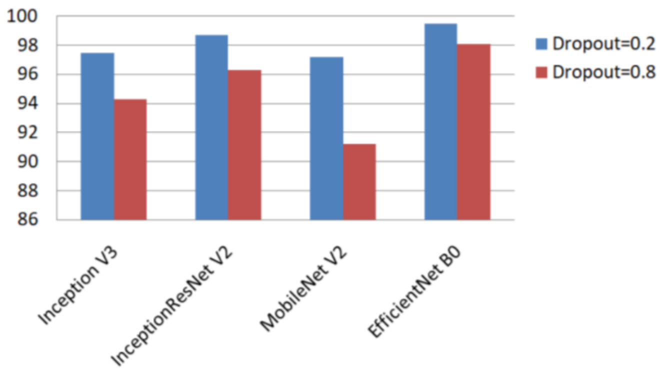


Fig. 6. With various dropout values, performance accuracy.

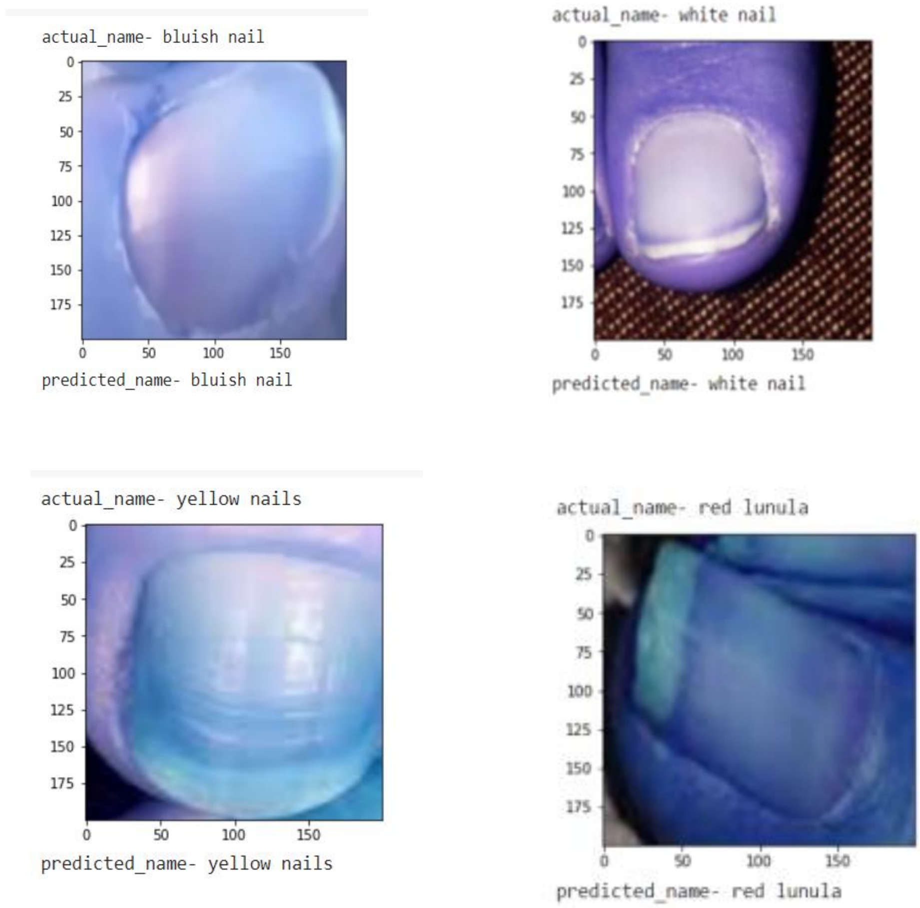


Fig. 7. From the test image set, an example of correct classification.

5. Conclusion

Many new approaches have been created for detecting and classifying human diseases using sick nail images. However, there is yet no reliable and cost-effective commercial method for diagnosing illnesses. We used four different DL models to make preliminary illness predictions (InceptionV3, InceptionResnetV2, MobileNetV2, EfficientNetB0). We used the Nail image dataset with 750 photos to train and test the model, with 90% training and 10% testing. With the EfficientNetB0 model, We were successful in our mission to reach the highest accuracy rate of 99.56 %.

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