International Journal of Early Childhood Special Education (INT-JECSE)
DOI:10.48047/intjecse/V14I8.401 ISSN: 1308-5581 Vol 14, Issue 08 2022

Cow Disease (LSD) Classification System for predicting different Severity levels.

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ABSTRACT
Lumpy Skin Disease is identified as a major threat to cattle production. It has a substantial impact on livelihoods and food security globally across the different countries in the world. Large skin nodules covering all parts of the body, fever, nasal discharge, spread lymph nodes and lacrimation are identified as the symptoms for this Lumpy skin disease. The virus responsible for this disease may spread due to direct contact to the skin lesions, saliva, nasal discharge, milk, or semen of cattle/animals infected by this disease. Unfortunately, there are no specific antiviral drugs or medicines available so far for the control and treatment of this Lumpy Skin Disease. The only mechanism available for control and treatment is the supportive care of cows. Thus, early detection helps to provide treatment before reaching the abnormal conditions. However, manual diagnosis and detection takes a significant amount of time and requires a trained professionally qualified and experienced person. Therefore, Artificial Intelligence based technology is needed to prevent and stop the animal disease epidemics. In this research work, we have proposed a classification system based on deep learning for predicting the different severity levels or grades of Lumpy Skin Disease. The proposed system uses a dataset of images of LSD-infected cattle, which have been labelled based on severity as mild, severe, and normal level by Veterinary doctors. We have utilized different pre-trained convolutional neural network (CNN) models customized by adding new layers for training by using the features extracted from the images. The trained model is then used to predict the severity levels of new Lumpy Skin Disease infected cattle images. We have evaluated the performance of our proposed system on a test dataset and achieved a high accuracy rate of 0.9182%. We have also compared our results across different models such as VGG19, Inception V3, Xception, ResNet50, DenseNet121 and MobileNetV2 and have demonstrated the superiority of our approach. Our proposed system has the potential to be used as a diagnosing tool for early detection and classification of LSD in cattle, enabling dairy farmers to take appropriate measures to prevent the spread of the disease and alleviate its impact.

KEYWORDS: *Augmentation, Classifier model, Lumpy Skin Disease, Pre-trained CNN models, Mobile Net V2*

1. INTRODUCTION

Lumpy Skin Disease is one of the serious deadly skin diseases caused by lumpy skin disease virus among cows. This Lumpy Skin Disease is characterized by fever, enlarged lymph nodes, firm and circumscribed nodules in the skin particularly visible in the hairless areas. Lumpy skin disease is currently endemic in most countries whose economy depends on cattle and milk production. It is an animal viral disease which causes several economic problems including significant milk yield loss, infertility, abortion, trade limitation and sometimes death.

Lumpy skin disease detection and classification based on different severity stages or levels using artificial intelligence is an untouched area. To reduce livestock mortality rate due to skin diseases, early-stage detection of this skin disease is very important. The use of deep learning for severity level classification will aid the animal health industry in reducing the spread of this disease. So, the motivation of this work is to contribute towards the achievement of lumpy skin disease detection and classification

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automatically by using deep learning models. The proposed system will use deep learning models for feature extraction and classification.There are three stages in LSD according to the number of lesions visible. 15 lesions are considered as a threshold where less than 15 are considered mild cases and more than are categorized as severe. Figure 1 shows the different severity levels in LSD disease.

- No visible nodules: Normal
- Few lesion nodules: Mildly infected
- Multiple lesions nodules: Severely infected

The other symptoms include high fever, reduced milk production, skin nodules, loss of appetite, increased nasal discharge and watery eyes, too much salivation and discharge of water from eyes and nose formation of nodules on the body.

Mild Severe Normal

Figure 1.The different severity levels in LSD disease.

2. LITERATURE SURVEY

Livestock is one of the critical socioeconomic assets in developing countries like India. However, the lack of a reliable and timely diagnosis system for identifying livestock diseases has led to significant losses in the livestock population, hindering efforts to achieve food security and reduce poverty in the country. To address this issue, a study proposed the integration of an expert system with machine learning and image processing was done by V.Lavanya et. al [16]. Haseena Thasneem et.al [2] have compared different algorithms for the segmentation of skin lesions in dermoscopic images. The basic segmentation algorithms are compared by using elapsed time as the metrics for comparison. Samuel Akyeramfo-Sam et.al [10] have proposed a web-based skin disease detection system named medilab-plus using a convolutional neural network classifier built upon the Tensorflow framework for detecting (atopic dermatitis, acne vulgaris, and scabies) skin diseases. Li-sheng Wei et al. [6] have done analysis on skin disease recognition method based on image color and texture features.They have proposed a method for skin disease detection and classification using a grey-level co-occurrence matrix (GLCM) method to segment images of skin disease and then they have used a support vector machine (SVM) classification method, and three types of skin diseases were identified. Finally, their method recognized three types of diseases, namely, herpes, dermatitis, and psoriasis. Sumithra et al. [15] have conducted an experiment for automatic segmentation and classification of skin lesions. They have prepared a dataset of 726 lesion samples from 5 different classes of skin diseases images collected through the internet. They have developed a computer vision-based system for segmentation and classification of skin lesions along with extraction of discriminating sets of features from skin lesions for efficient classification. Initially they segmented the lesion areas using region growing method, and then Colour and texture features are extracted to represent the segmented lesion areas. Then the classification is performed with SVM, KNN as well as fusion of SVM and KNN Classifiers. Sam, Philip et. al [9] have conducted research on a web based skin disease diagnosis using conventional neural networks. This study sought to propose a web-based skin disease detection system named medilab-plus using a convolutional neural network classifier built upon the Tensorflow framework. The integration of an expert system with deep learning image processing was proposed by Bezawit Lake et. al [3]. The cattle disease symptoms that were visible to the naked eye were collected by a cell phone camera. Symptoms that were identified by palpation were collected by text dialogue. The identification of the symptoms category was performed by the image analysis component using a convolutional neural network (CNN) algorithm. The algorithm classified the input symptoms with 95% accuracy. Elias Girma et. al [4] have used pre-trained models to extract features and trained using machine learning. In this work, an algorithm is described for animal Lumpy

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skin disease detection and classification. They used Convolutional Neural Networks for feature extraction and SOFTMAX, RF and SVM classifiers for Classification. This study involves data set preparation for training and testing Lumpy Skin Disease classification model. Ammara Masood et. al [1] have compared the performance of several classifiers specifically developed for skin lesion diagnosis and discussed the corresponding findings. They have also indicated various conditions that affect the technique's performance. They have also suggested a framework for comparative assessment of diagnostic models and reviewed the results based on these models.

Md. Rony et. al [7] have proposed models to early detect the most common external diseases using several CNN architectures like conventional deep CNN, Inception-V3, and VGG-16 in the field of deep learning. All necessary steps for performing the disease detection model are completely described in their work from the data collection to the process and outcome. The proposed system has results with 95% accuracy, which may reduce human errors in the identification process and will be helpful to recognize diseases for veterinarians and husbandry farmers. N. Alamdar et. al [9] have studied detection and classification of acne lesions in acne patients, which focused on common chronic skin disease. The aim of this work is to find a proper computational imaging method for automatic detection of acne using images that are taken by cell phone and then the classification of the different types of acne lesions from each other.Kumar V.B et. al [5] have conducted research on dermatological disease detection using image processing and machine learning. Their research used a dual stage approach which combines computer vision and machine learning on clinically evaluated histopathological attributes to accurately identify the disease. In the first stage, the image of the skin disease is subject to various kinds of pre-processing techniques followed by feature extraction. The second stage involves the use of machine learning algorithms to identify diseases based on the histopathological attributes observed on analysing the skin. Nonlinear models like ANNand DL learn the underlying pattern and give better accuracy. But the system suffers from inaccuracies when it is tasked with detection of diseases on varying skin colours. Shivangi Jain et. al [12] have presented a computer aided method for the detection of Melanoma Skin Cancer using Image Processing tools. The input to the system is the skin lesion image and then by applying novel image processing techniques, they have analysed the presence of skin cancer. The Lesion Image analysis tools checks for the various Melanoma parameters Like Asymmetry, Border, Colour, Diameter, (ABCD) etc. by texture, size and shape analysis for image segmentation and feature stages. The extracted feature parameters are used to classify the image as Normal skin and Melanoma cancer lesion. Seeja R D et. al [11] have developed a system to improve the classification performance of melanoma using deep learning based automatic skin lesion segmentation. It can assist medical experts on early diagnosis of melanoma on dermoscopy images. Zhen Ma et. al [18] have proposed a level set method to fulfil the segmentation of skin lesions presented in dermoscopic images. The proposed algorithm is robust against the influences of noise, hair, and skin textures, and provides a flexible way for segmentation. Numerical experiments demonstrated the effectiveness of the novel algorithm. Mehak Arshad et. al [8] have proposed a new automated framework for multiclass skin lesion classification by extracting features and performing fusion using a modified serial-based approach. Finally, the fused vector is further enhanced by selecting the best features using the skewness controlled SVR approach. The final selected features are classified using several machine learning algorithms and selected based on the accuracy value. Sonawane et. al [14] have proposed 4 different phases composed of pre-processing, segmentation, feature extraction, and classification. To accomplish each stage, various digital image processing and machine learning techniques are used and achieved 90 to 95% accuracy using a Support Vector Machine. Result of their CAD technique is used to support the doctor to easily find out a detected area contains symptoms or lesions as compared to other techniques.

3. PROPOSED METHODOLOGY

The proposed methodology consists of three functional blocks namely feature extractor, Training model and Classifier. The feature extractor is designed by using pre-trained CNN models by removing the top layer. 6000 LSD images from the 3 different levels of the disease namely Mild, Normal and Severe

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are given to the feature extractor for feature extraction. The training and validation images are given to the feature extractor for feature extraction. The extracted features are applied as input to the training model designed by using shallow neural networks to create the trained model. The result of the training process will also generate training accuracy, validation accuracy, training loss and validation loss. The image to be tested for any one of the severity levels of the disease class is given to the classifier as input for performing the classification along with the trained model. The classifier will output the result as a correct or incorrect prediction. The classifier results are used to find the number of correct and wrong predictions in the LSD images. The results obtained from the classifier are observed and compared among them to identify the best classifier designed with the pre-trained CNN models. The classifier whose performance metrics are verified as the best one can be recommended to the eye specialists to diagnose the three different severities of the diseases.

The purpose of Feature Extractor in the automatic LSD classifier is to transform the raw images into limited distinct features to reduce the complexity in processing the images without losing the meaningful information. Pre-trained neural network models are used for this purpose. The Feature Extractor extracts the unique features in the training and testing images to form the unique vector for all the images in the training and testing data. The feature extraction transforms the labelled LSD images into labelled feature vectors. Feature Extraction also helps to avoid the large amount of memory requirement and computing power. The labelled feature vectors are used as inputs to the training model to learn the features effectively and generate a trained model with optimum weights. Feature extractor also avoids the classifier to overfit to training images and to generalize poorly to new images. A shallow neural network whose input sizes are the same as the size of the feature vector is used as the input layer in the training model. The amount of time used for training the model will vary based on the pre-trained model that is used to create the feature extractor. The best trained model which has the maximum validation accuracy is obtained after the training process to be used by the classifier during classification. Figure 2 represents the proposed methodology used for LSD classifier.

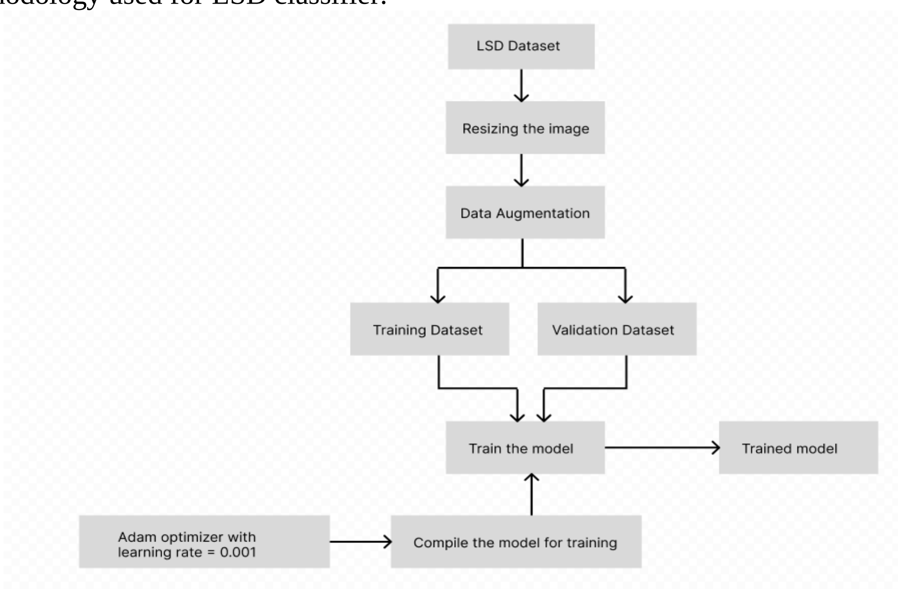

Figure 2.Proposed methodology for LSD classifier

The conventional feature descriptors will extract only some specific features in the LSD images. These features may not be sufficient to detect a specific severity level of the disease precisely. The accuracy of these feature extractors is not sufficient to use them for feature extraction. Therefore, there is a need for a model that can extract all the features corresponding to a specific level of the disease class. The pre-trained CNN models are selected for feature extraction with the aim of extracting all the relevant

DOI:10.48047/intjecse/V14I8.401 ISSN: 1308-5581 Vol 14, Issue 08 2022

features in the LSD images by using the different convolution layers in the CNN model. The lower layers will extract the low-level features and the middle layers will extract the mid-level features. Finally, the end layers will use all these features to create the high-level features corresponding to the disease class.

3.1 FEATURE EXTRACTOR

It was proved and identified that pre-trained CNN models were a good feature extractor for a completely new task/problem. The designed feature extractor will extract useful attributes from an already trained CNN with its trained weights by feeding our image data having different severity of the diseases on each level and tune the CNN a bit for the specific task namely for the severity of the disease classification. The convolution process in the CNN can extract the relevant information at low computational costs. Thus, the pre-trained CNN is selected for feature extraction after considering their merits over conventional NNs and ANN. The pre-trained CNN models will detect key points on the image and the number of key points will vary from image to image. Then a feature vector is built for each image based on the number of key points used for representing the image. The features extracted from the images in the form of feature vector are used for further training the model that is constructed by using shallow neural networks.

3.2 TRAINING MODEL

The shallow neural network used for training the model is designed with an input layer having the same shape as that of the feature map or size extracted by the feature extractor.The convolution operation is performed by a different convolution layer of CNN by using a filter or kernel of some size. Then the core building block of CNN, namely the convolution layer with a set of learnable filters is added to the input layer as the first stack. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the corresponding pixels in the input image and producing the 2-dimensional activation map of that filter. Thus, the network makes the filter to learn, and the filter gets activated when it detects some specific type of features at some spatial position in the input image. The full output volume of the convolution layer is formed by stacking the activation maps for all the filters along the depth dimension.

During training, half of the neurons on the convolution layer are deactivated. This is done specifically to improve generalization. This will force the neural network layer to learn the same concepts but with different neurons. The idea behind dropout is to trade the training performance for more generalization and to avoid overfit. After dropping the 50% of the neurons, the flattening operation is applied to convert the output vector into a 1-D vector. Flattening uses all its structure to create a single long feature vector to be used by the output dense layer for further classification. The flattening step is needed to make use of the fully connected layers after convolution. Flattening performs a function mapping from the output of filters used in the convolution layer into a feature vector. The Dense layer is added as the last layer in the training model used for training. Normally, the dense layer in the three different severity levels of the disease classification problem will use the “3-way softmax” as activation function which produces a probability distribution over 3 classes.

3.3 LSD CLASSIFIER

The same pre-trained model that was used for feature extraction is also used for designing the classifier. The trained model obtained in the form of optimum weights during training is applied as input to the

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classifier along with the image to be classified. The image is predicted by finding

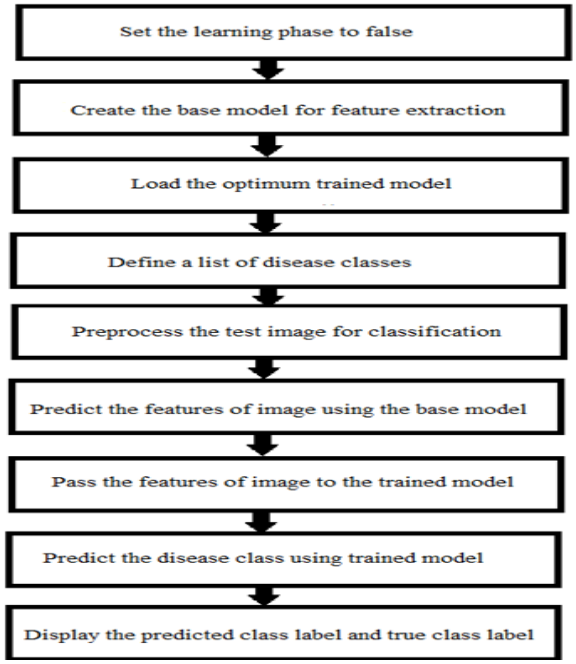

Figure 3. Different steps involved in classification.

the actual class index value and the actual class name for each image given to the model by using the weights of the pre-trained model.

4. RESULTS AND DISCUSSION

4.1 CONFUSION MATRIX FOR SIX DIFFERENT CLASSIFIERS

The 6 LSD classifier outputs are shown by using the confusion matrix from Figure 4.1 to 4.6.

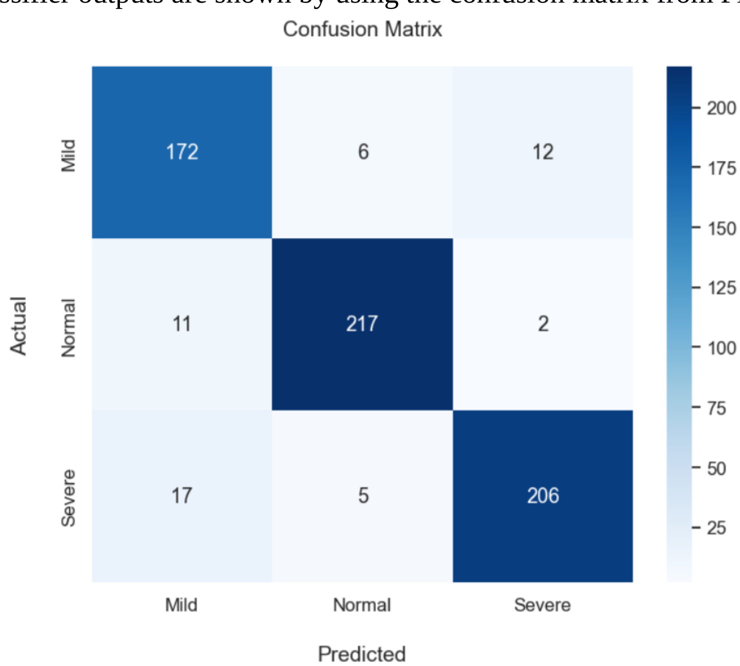

Figure 4.1Confusion matrix LSD disease classifier designed with MobileNetV2.

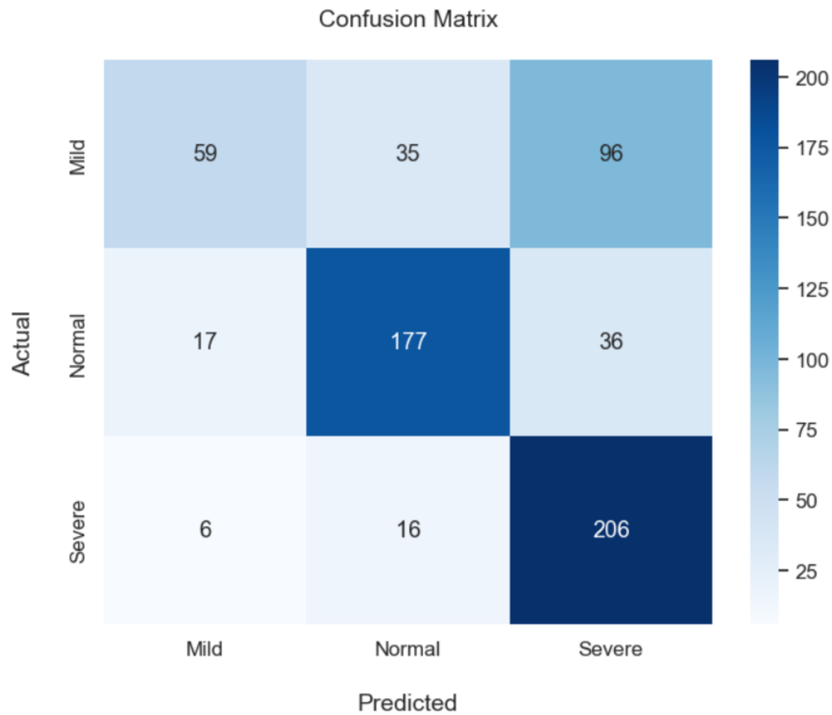

Figure 4.2 Confusionmatrix for LSD classifier designed with VGG19.

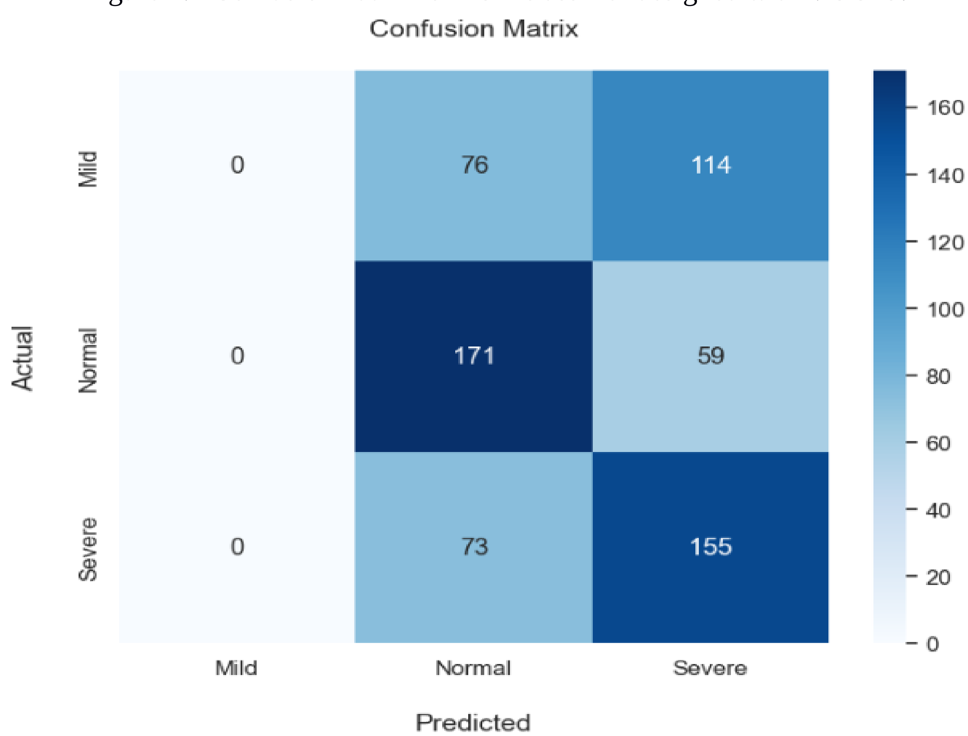

Figure 4.3 Confusion matrix for LSD classifier designed with Resnet50.

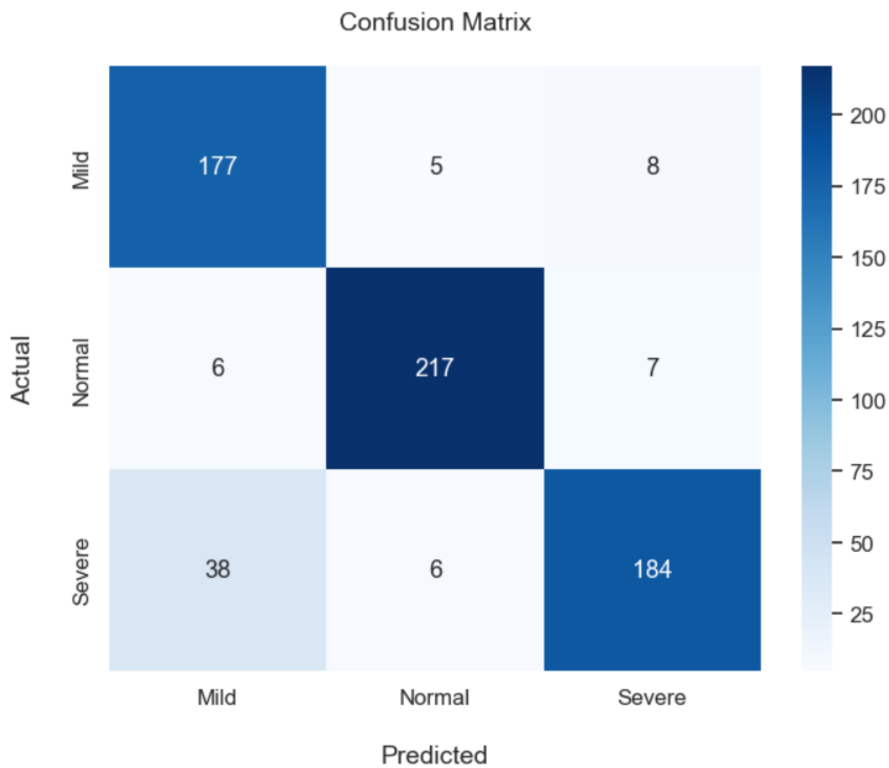

Figure 4.4 Confusion matrix for LSD classifier designed with Xception.

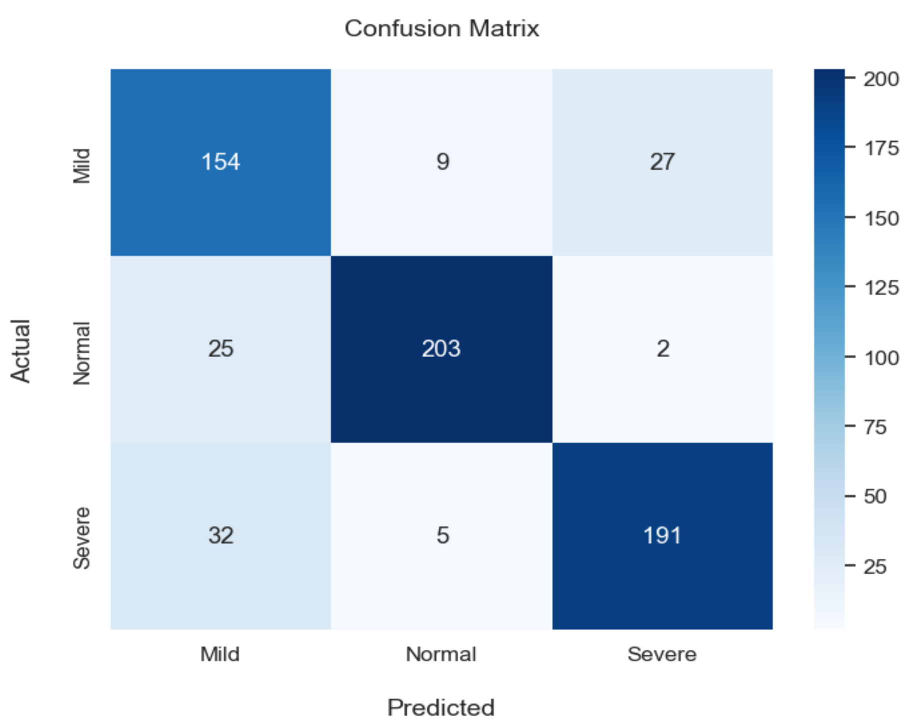

Figure 4.5 Confusion matrix for LSD classifier designed with DenseNet 121

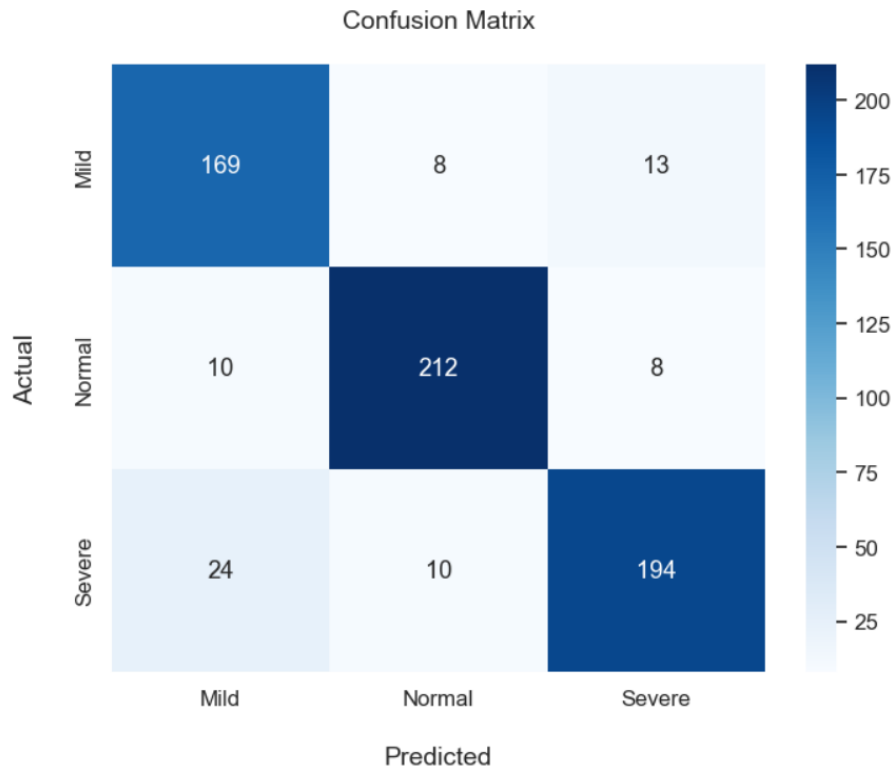

Figure 4.6Confusion matrix for LSD classifier designed with InceptionV3.

5.1 PERFORMANCE STATISTICS ANALYSIS FOR LSD CLASSIFIER

The overall performance of six different models for six different performance metrics were tabulated in Table 5.1 for analysis and to identify the best model.

Table 5.1Overall performance statistics analysis for LSD Classifier

CNN Models	Kappa	Overall accuracy	PPV_Macro	PPV_Micro	TPR_Macro	TPR_Micro
DenseNet121	0.7683	0.8456	0.84451	0.84568	0.84362	0.84568
MobileNetV2	0.8770	0.9182	0.9160	0.9182	0.9174	0.9182
VGG19	0.5142	0.6820	0.7017	0.6821	0.6612	0.6821
Inception V3	0.8280	0.8873	0.88294	0.88576	0.88553	0.8857
Xception	0.8380	0.8919	0.8924	0.8919	0.8940	0.8919
ResNet50	0.2315	0.50309	None	0.50309	0.47443	0.50309

5.1.1 PERFORMANCE ANALYSIS USING KAPPA

Kappa statistics is a measure of how closely the instances or classes or labels classified with pre-trained CNN model matched the data labelled as ground truth by the experts and thuscontrolling the accuracy of a classification model as measured by theexpected accuracy. The strength of agreement of the model can be recommended based on the values of kappa as very good, good, moderate, fair and poor as tabulated in Table 3 as mentioned by Sivamurugan Vellakani et. al [13]. Classification models which have used MobileNetV2 as feature extractor have maximum kappa value equal to 0.8770 as shown in Figure 5.1.

Table 5.2 Kappa value and the corresponding strength of agreement

Kappa Value	Strength of Agreement
<0.20	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.0	Very Good

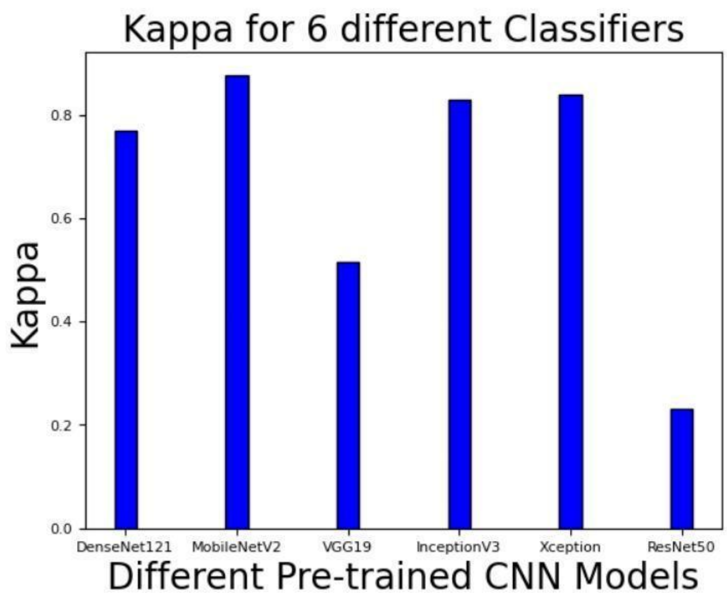

Figure 5.1 Comparison of kappa value of 6 different Pre-trained CNN models

5. 1.2 PERFORMANCE ANALYSIS USING OVERALL ACCURACY

The Overall Accuracy of the model is computed by dividing the sum of the correct predictions from all the classes of severity levels divided by the total number of images belonging to all the classes of severity levels. The overall accuracy is equal to 0.9182 for the classification model that was designed with MobileNetV2 as feature extractor as shown in Figure 5.2. This is also evidence for suggesting these image classification models to the Veterinary doctor for supporting their clinical decision in classifying the different levels of severity in lumpy skin disease.

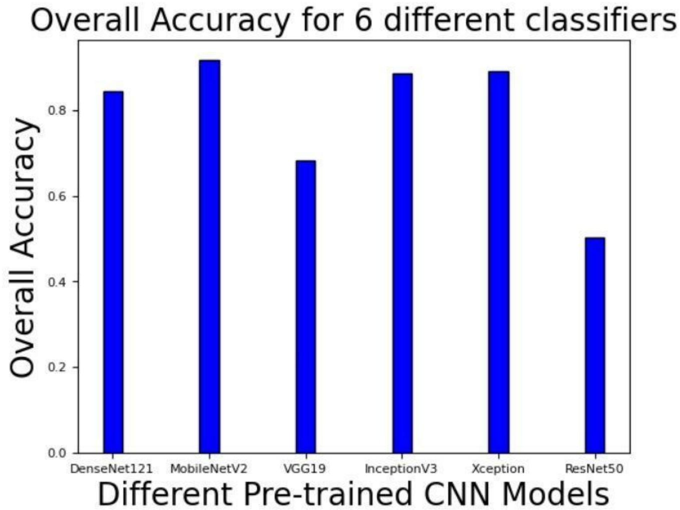

Figure 5.2 Comparison of Overall Accuracy of 6 different Pre-trained CNN models

5.2 INDIVIDUAL PERFORMANCE STATISTICS ANALYSIS FOR EACH SEVERITY LEVELS

Image classification systems with minimum validation loss can be compared with each other to select the best caption generator based on the benchmark results. For each of the 3 classes, 6 different metrics are computed. They are Accuracy, F1Score, F2Score, Precision or Positive Predictive value. Our experiments have demonstrated that classification models designed using MobileNetV2 pre-trained CNN model have shown good performance in predicting the symptoms for all the 3 classes. The Tables 5.3 to 5.5 are used to show the individual performance statistics analysis for each LSD disease class.

Table 5.3Individual performance statistics analysis of the pre-trained CNN models for mild class

CNN Models	**Accuracy**	**F1 Score**	**F2 Score**	**Precision**
DenseNet121	0.85648	0.76808	0.793	0.72986
MobileNetV2	0.92901	0.88205	0.89583	0.86
VGG19	0.76235	0.43382	0.35036	0.71951
Inception V3	0.91393	0.85333	0.87146	0.82474
Xception	0.91204	0.8613	0.90214	0.8009
ResNet50	0.70679	0.0	0.0	None

Table 5.4Individual performance statistics analysis of the pre-trained CNN models for normal class

CNN Models	**Accuracy**	**F1 Score**	**F2 Score**	**Precision**
DenseNet121	0.93673	0.90828	0.8927	0.93548
MobileNetV2	0.96296	0.9476	0.94512	0.95175

DOI:10.48047/intjecse/V14I8.401 ISSN: 1308-5581 Vol 14, Issue 08 2022

VGG19	0.83951	0.77293	0.77091	0.77632
Inception V3	0.94366	0.92174	0.92174	0.92174
Xception	0.96296	0.9476	0.94512	0.95175
ResNet50	0.67901	0.6218	0.6895	0.5343

Table 5.5Individual performance statistics analysis of the pre-trained CNN models for severe class

CNN Models	**Accuracy**	**F1 Score**	**F2 Score**	**Precision**
DenseNet121	0.89815	0.85268	0.84364	0.86818
MobileNetV2	0.94444	0.91964	0.90989	0.93636
VGG19	0.76235	0.72792	0.824	0.60947
Inception V3	0.91393	0.87585	0.86069	0.90233
Xception	0.90895	0.86183	0.82808	0.92462
ResNet50	0.62037	0.5575	0.625	0.4725

5.2.1 PERFORMANCE ANALYSIS USING ACCURACY FOR EACH CLASS

All trained models except the one designed with MobileNetV2 as feature extractor are perfect in predicting the LSD disease accurately and their accuracy of prediction is to 0.91. The other models designed with Xception, InceptionV2 as feature extractors have accuracy of caption generation equal to 0.89 and 0.88 respectively.

5.2.2 PERFORMANCE ANALYSIS USING F1 SCORE

F1Score is defined as the harmonic mean of precision and recall. Therefore, F1Score will consider both false positives and false negatives. If we have uneven class distribution in the number of images used in the training process, then F1 Score is more useful than accuracy. One model that has used MobileNetV2 for feature extraction has an F1 Score equal to 0.91964 when predicting the classification for the classes accurately. F1 Score is a significant metric used for comparing the performance of the model when the number of images in each class is not the same when used for training the model.

5.2.3 PERFORMANCE ANALYSIS USING F2 SCORE

F2Score is defined as the weighted average of precision and recall. Therefore, F2Score will consider both false positives and false negatives. If we have uneven class distribution in the number of images used in the training process, then F2 Score is more useful than accuracy. F2 Score is effective in classification when the cost of false negative is much higher than the cost of false positive. 2 image classification models having F2 Score more then to 0.81 when generating captions for the severity levels accurately are designed with the pre-trained CNN models namely ResNet50, InceptionResNetV2 for extracting the features to be used during the training of the model. The image caption generation systems which are based on MobileNEtV2is found to have F2 Score close to 0.90989.

5.2.4 PERFORMANCE ANALYSIS USING PRECISION OR POSITIVE PREDICTIVE VALUE (PPV)

Precision is calculated by dividing the number of correct positive predictions by the total number of positive predictions. It is also called positive predictive value (PPV). The best precision value is 1.0, whereas the worst value is 0.0. Four caption generator models are having precision equal more than 0.83

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when predicting the image caption description for severity level classes accurately. One neural caption generator model that are designed with MobileNetV2 as feature extractor has precision almost very close to 0.94 when predicting the captions for all the 3 classes.

6. CONCLUSION

The experimental observations have proved that the trained model designed using the pre-trained model MobileNetV2 had better performance when compared with the trained models designed using other pre-trained models. Therefore, the trained model designed using MobileNetV2 can be used for predicting the different severity levels of lumpy skin disease. This model can also be recommended to the Veterinary doctor as an aiding tool for diagnosing the lumpy skin disease.

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