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Skin Disease Detection Using Deep Transfer Learning Models And Image Processing

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Abstract
Skin diseases are far more common diseases than other body related diseases. It often get neglected by people. Diseases range from common dermatological concerns to rare and complex disorders, that can also leads to cancerious diseases. So the detection and diagnosis of such complex and vast disease is a huge task. This creates a significant burden on healthcare systems.Tradional method of detecting disease is bit time consuming and it may leads to inaccurate results due to visual similarities among diferent diseases. This study suggests a deep learning and image processing-based automated skin disease diagnosis system. The suggested method uses Skin Disease Dataset comprising images of 22 different types of skindiseases. It uses deep learning algorithms like Convolutional Neural Networks (CNN) and transfer learning models such as VGG16, VGG19, ResNet50V2, and MobileNetV2. The dataset images are preprocessed utilizing scaling, and transfer models are applied When compared to conventional CNN designs, experimental data show that transfer learning models greatly increase classification accuracy. ResNet50V2 gives 91.5 %and MobileNetV2 give 88.7 % and VGG 19 gives 90.1 % accuracy. The proposed system can assist doctors especially, dermatologists in fast diagnosis. This system can be included in real-time health apps for automated skin conditions screening.

Keywords: *CNN, Skin Disease, Image processing, Resnet50V2, MobileNetV2.*

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I. Introduction

Skin diseases

Skin is first body part that is prone to any disease.It protects the body from viruses, controls body temperature, and permits tactile sensations like heat, cold, and pain. It is the main interface between the human body and the outside world.

Dermoscopy or a physical biopsy are frequently performed after a doctor's eye examination, which is currently the norm for identifying these conditions. Subjectivity is this approach's main weakness. Because so many skin lesions have almost the same visual characteristics—differing just slightly in texture, borders, or color—a doctor's firsthand expertise is the only way to make an accurate diagnosis. This slows down manual screening and increases the possibility of human error. A delayed or inaccurate diagnosis of a malignant illness might have serious repercussions for the patient in areas with insufficient specialized dermatologists. Therefore, it is critical to develop dependable, automated computer systems to help medical practitioners with preliminary screening. In This Paper we have applied Custom cnn models on dataset comprising skin diseases divided into 22 categories that classifies diseases. Then machine runs and applies models namely, VGG16, VGG19, Resnet50V2 and MobileNetV2 that detects diseases. It is often a difficult task for dermatologists to differentiate between different diseases like eczema, actinic keratosis, tumors, melanoma, skin cancer, rosasia and etc .

II. Literature Review

A [1] Deep Long and Short-Term Memory with Tunicate Swarm Algorithm (DLSTM-TSA) was proposed for the identification and categorization of skin diseases. A[2] genetic algorithm-optimized stacking ensemble strategy for the identification.Method used a genetic algorithm to maximize the ensemble by combining many deep learning architectures. On the DermNet dataset, the suggested approach obtained 74%

Top-5 accuracy, and on the HAM10000 dataset, 80.47%accuracy. A System [3]proposed SCCNet, a deep CNN-based model for skin cancer detection and multi-class classification. The model achieved 93.08% accuracy on the ISIC-2019 dataset and outperformed several traditional ML and DL methods.A[4] Study aims to check performance of ResNet50, InceptionV3, EfficientNetB0, And VGG16 where ResNet gives accuracy of 93.5% and VGG with lowest performance of 84.32%. A [5] system of image processing–based system for leaf and skin disease detection using K-Means clustering and Support Vector Machine algorithms. Their approach focused on feature finding, segmentation, and disease classification using MATLAB. A[6] system for the detection and classification of skin diseases using gray level Co- occurrence matrix(GLCM) and decision tree ID3 algorithm.It achieves accuracy of 87% on 45 test images consisting three diseaseas namely, melanoma, eczema and leprosy.[7] CNN applied on metadata of pateint that involves feature like age ,sex,lesion location and ensemble which gives improved balanced multicalss accuracy on ISC/2018 test set reported balanced accuracy of 88.7% when used Multiclass SVM. A[8] traditional Multiclass Svm used on three types of diesease melanoma, ecsema and psoriasis on 20 imagedataset with accuracy of 85%. An [9] AI based skin disease diagnosis system that use segmentation to extract ROI from image and classifying image using DenseNet and EfficientNet but accuracy of model were poor with DensNet upto 3% and with EfficientNet it was 1%.A [10] Study examined the rise of Lumpy Skin Disease (LSD) in India. The disease's epidemiology, transmission, diagnosis, and treatment were all covered in their work. In order to control epidemics, the study focus on the significance of premature illness observation and monitoring systems.

III. Proposed Methodology

Convolutional Neural Network (CNNs) is applied in field of healthcare. We applied this in Skin Disease dataset comprising 1544 images collected from kaggle. That follows Feature extraction and classification.On Cnn architecture we applied VGG16, VGG19, MobileNetV2 and ResNet50v2 that detects disesase.

Dataset Description

The Skin Disease-dataset consists of total 1544 images that sourced from kaggle.The dataset contain 22 classes of different diseases namely, Acne, Actinic Keratosis, Benign Tumors, Bullous Candidiasis, Drug Eruption, Eczema, nfestations / Bites, Lichen, Lupus, Moles, Psoriasis, Rosac, Seborrheic Keratose, skin Cancer, Sun / Sunlight Damage, Tinea, Urticaria, Vascular Tumors, Vasculitis, Viral Infections Warts.
We have split dataset into two parts one that comprises 80 and 20 ratio for training set and other for testing set.

Training set includes 11,128 images and 2,770 images are reserved for validation purpose.also stored separate directory containg 1,546 test images.
The test data that we use it contains selected set of skin photos.

Image preprocessing

The first steps in the classification of skin diseases are often data collection and preparation since they guarantee a large dataset of photos of skin lesions with labels that go with it.To apply CNN model all images were resized to 224x224 pixels. Foe scaling of pixel data normalizing scale of 1/255.0 maintained for uniform extraction of feature data.

Baseline Custom Model

The model accepts RGB images of size 224×224×3as input. Three convolutional layers with 64, 64, and 128 filters respectively were employed to extract hierarchical image features. After every convolutional layer, MaxPooling layers with a 2x2 pool size were used to lower computational cost and spatial dimensions. The collected feature maps were run through fully connected dense layers with 128, 64, and 64 neurons after being flattened into a one-dimensional vector. To lessen overfitting and enhance generalization performance, a[16]dropout layer with a dropout rate of 0.4 was added. Lastly, a Softmax output layer with 22 neurons was employed for skin disease multi-class categorization[16]. With 11.2 million trainable parameters, the total architecture efficiently learns discriminative lesion features for precise disease prediction. forecasts the likelihood of each type of skin condition.

Improved Custom CNN Model

This model accepts RGB photos with dimensions of 224 x 224 x 3. Four convolutional blocks with 32, 64, 128, and 256 filters, respectively, were used for extraction. To maintain spatial dimensions, each convolution operation used a 3x3 kernel with ReLU[15] activation and the same padding. To stabilize training and accelerate convergence, batch normalization layers were added after each convolutional layer. Feature map dimensions and computational cost were decreased by using MaxPooling layers with a 2x2 pool size. To decrease the amount of trainable parameters and enhance generalization performance, Global Average Pooling

was used in place of a flatten layer. To reduce overfitting, dropout layers with dropout rates of 0.5 and 0.3 were added[11]. Finally, a fully connected dense layer with 128 neurons and a[16] Softmax output layer were used for [17] multi-class classification of skin diseases.

IV. Transfer Learning Models

VGG16

At University of Oxford in 2014 Visual Geometry Group introduced VGG convolutional neural network design[12]. The model became famous because it proved that depth matters — stacking more layers significantly improves learning, even if each layer is simple. VGG16 was designed for the ImageNet dataset, which contains over 14 million images and 1,000 categories, ranging from animals to vehicles to household objects[12]. VGG16 receives 224x224x3 dermoscopic skin pictures as input. The include_top=False parameter is used to import ImageNet weights into the pre-trained VGG16 convolutional base, eliminating the original fully connected classification layers while keeping the convolutional feature extraction layers. Multiple stacks of convolution and max-pooling processes make up these convolutional layers, which gradually learn hierarchical image representations from low-level characteristics like edges and textures to high-level semantic information like aberrant skin patterns and lesion architecture. all layers of the VGG16 convolutional base are frozen by setting the trainable parameter to False.Which prevents modification of the pre-trained ImageNet weights during training and allows the model to utilize VGG16 as a fixed feature extractor. The VGG16 convolutional base produces deep feature maps with dimensions of 7x7x512. Rich geographical and semantic information about the characteristics of skin lesions can be found in these feature maps. The three-dimensional feature maps are then transformed into a one-dimensional feature vector with 25,088 features using a Flatten layer. Dense layer containing 256 neurons with ReLU activation is employed to learn nonlinear relationships among the extracted lesion features. The ReLU activation function introduces nonlinearity into the network and improves training efficiency by eliminating negative activations. Softmax output layer containing 22 neurons corresponding to the skin disease classes is utilized for [17] multi-class classification. The [16]Softmax activation function converts the network outputs into probability distributions, where the class with high probability.

VGG 19

VGG-19 is a deep convolutional neural network with 19 weight layers, comprising 16 convolutional layers and 3 fully connected layers[12]. VGG-19 is built around stacks of convolutional layers that use small 3x3 filters with a stride of 1 and same padding so the spatial size of the feature maps stays intact[12]. After every convolution, they apply ReLU activation to add non-linearity[15]. To shrink the dimensions step by step, max-pooling layers with 2x2 windows and stride 2 are used at regular points. Towards the end, the network has three fully connected (dense) layers for classification, and finally[16] a softmax layer that gives the probability scores for each class.

A transfer learning approach based on the pre-trained VGG19 model was implemented for multi-class skin disease classification. The VGG19 architecture pre-trained on the [16] ImageNet dataset was utilized as a feature extractor by removing its original fully connected classifier layers using include_top=False. All convolutional layers were frozen to preserve the learned ImageNet feature representations and reduce computational complexity. The extracted feature maps of size 7×7×512were flattened into a one-dimensional feature vector and passed through a dense layer containing 256 neurons with[15] ReLU activation. A [16]Softmax output layer corresponding to 22 disease classes is used for final classification.

ResNet50V2

ResNet50V2 is a 50-layer deep convolutional neural network, part of the ResNet-V2 family, designed for image recognition tasks. It improves upon the original ResNet50 by rearranging batch normalization and ReLU activation, resulting in better accuracy on datasets like ImageNet. ResNetV2 improves the flow of information by applying Batch Normalization and ReLU activation before the convolution layer, rather than after.

The fully connected classification layers of the ResNet50V2 model, which was pre-trained[16] on the ImageNet dataset, were eliminated using include_top=False in order to use it as a feature extractor. To minimize computational complexity and maintain the learnt ImageNet feature representations, all convolutional layers were frozen. In order to improve deep feature learning and get over the vanishing gradient issue, the architecture makes use of residual skip connections. The 7x7x2048 extracted feature maps were compressed using a Global Average Pooling layer before being sent through a thick layer with 256 [15]ReLU-activated neurons. The final categorization was done using a Softmax output layer that represented 22 illness classifications.

MobileNetV2

MobileNetV2 is a CNN architecture optimized for mobile and embedded vision applications. It improves upon the original MobileNet by introducing inverted residual blocks and linear bottlenecks, resulting in higher accuracy and speed while maintaining low computational costs[13]. MobileNetV2 is widely used for tasks like image classfication, object detection and image segmentation on mobile and edge devices[13]. Dermoscopic skin photographs with dimensions of 224 x 224 x 3 are accepted as input by the MobiletNetV2. To maintain the learned ImageNet feature representations and minimize computational cost during training, every convolutional layer in the MobileNetV2 architecture is frozen. The architecture makes use of inverted residual bottleneck blocks and according to depth separable convolutions, which greatly lower the number of parameters and increase computing efficiency without sacrificing the capacity to extract features effectively[13]. The MobileNetV2 convolutional basis produced extracted feature maps with dimensions of 7x7x1280. The feature maps are compressed into a one-dimensional feature vector using a Global Average Pooling layer, which minimizes overfitting and uses less memory. In order to discover nonlinear interactions among skin lesion features, the compressed data are subsequently fed via a fully linked dense layer made up of 256 neurons with [15]ReLU activation. Lastly, for[17] multi-class classification, a[16] Softmax output layer that corresponds to 22 skin disease classes is used.

V. Training Parameters

All the models compiled using [14]Adam optimiser and Categorical Cross-Entropy loss. Models are subjected to analysis and evaluate based on metrices like accuracy,recall and precision that are given below in figure 1.

Parameter	Value
Input Size	224×224 pixels
Batch Size	32
Optimizer	Adam (lr=0.0001)
Loss Function	Categorical Crossentropy
Train-Val Split	80/20
Max Epochs	20-30 with Early Stopping
Metrics	Accuracy, Precision, Recall

Figure1.

These terms are helpful below figure2.[19]

Term	Meaning
True Positive(TP)	Accurately identifying sickness of person
True Negative(TN)	Accurately identifying person does noty have sickness.
False Positive(FP)	Misidentify a person having as illness when they don't.
False Negative(FN)	Incorrectly Identifying a person as not have disease when they have.

Figure 2.

Accuracy

It [19] means the number of samples identified correctly divided by the total number of samples in dataset.

Accuracy = TP+TN/TP+TN+FP+FN [19] (1)

Recall

It is the percentage of all correctly detected positive samples that are suitably recognised from dataset.

Recall = TP/TP+FN (2)

Precision

Precision means the proportion of correctly identified positive samples among the total number of predicted positive sample.

Precision = TP/TP+FP (3)

Equations (1to 3) are formulas.

VI. Results And Discussion

Environmental Setup

The proposed skin disease detection system was implemented in a Python-based deep learning environment using [18]TensorFlow and Keras frameworks. The experiments were executed on a GPU-supported system for efficient training and evaluation of CNN and transfer learning architectures. Image preprocessing, data enhancement model training, and performance analysis were performed using standard scientific computing and visualization libraries.

Model Comparison

Explained in fugure 3.

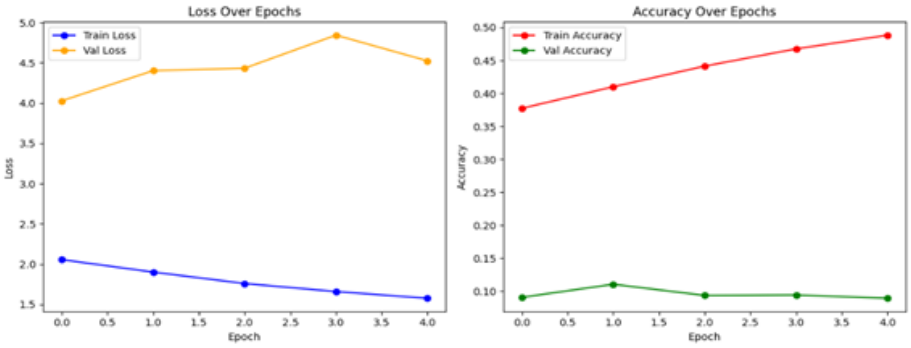
Model	Accuracy	Precision	Recall
Baseline CNN model	78.5%	75.2%	76.8%
Improved CNN model	82.3%	79.8%	81.2%
VGG16	89.2%	87.5%	88.9%
VGG19	90.1%	88.4%	89.7%
ResNet50V2	91.5%	89.8%	90.6%
MobileNetV2	88.7%	86.9%	87.8%

Figure3.

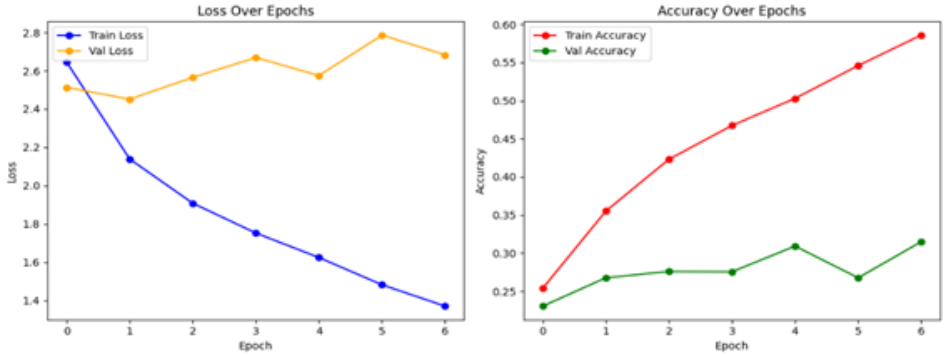
Graphical analysis of models based on Epoch Value

We have plotted graphical values with batch size 32 and epoch value upto 30.

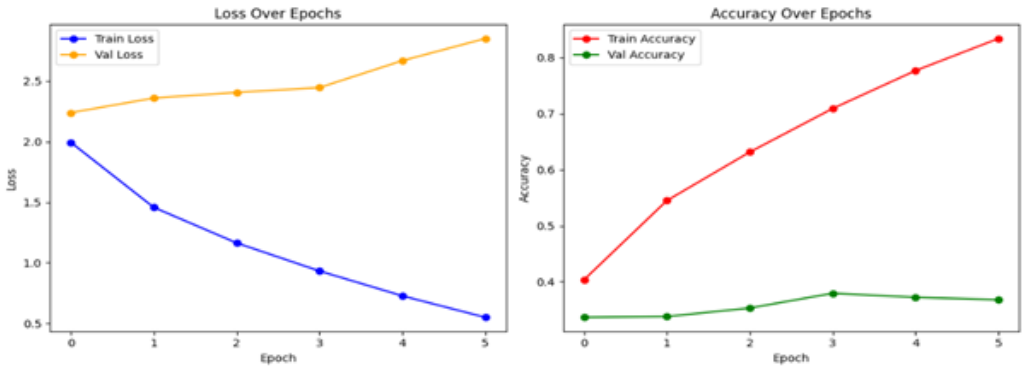
VGG16



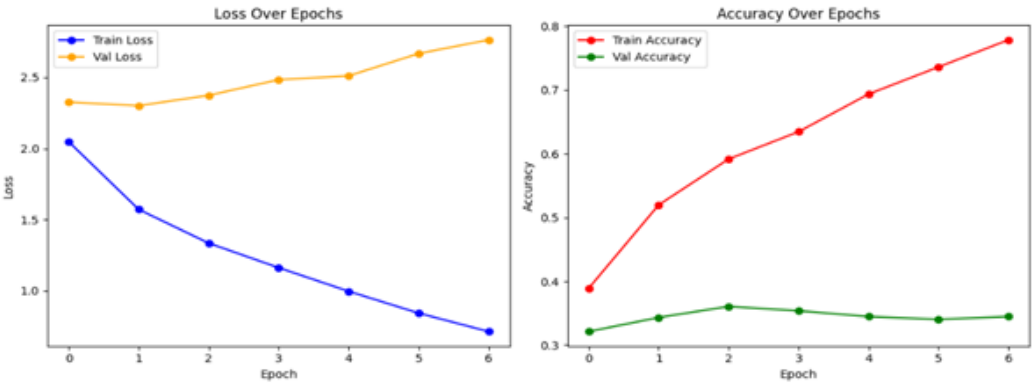
Vgg19



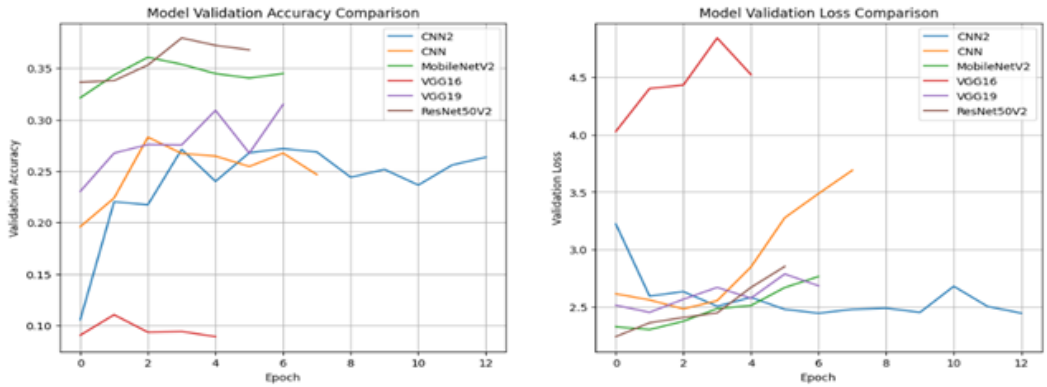
Resnet50V2



MobileNetV2



Comparison of Models



VII. Conclusion

This research presented a deep learning-based system for automated skin disease detection using image processing techniques. Multiple CNN and transfer learning models were implemented and compared for multiclass skin disease classification. Experimental analysis demonstrated that transfer learning models that includes VGG19 ,ResNet50V2 and MobileNetV2 achieved superior performance due to their advanced feature extraction capabilities.ResNet give accuracy of 91.5% and MobileNetV2 gives accuracy of 88 %.VGG19 Achieved 90.1 % accuracy. The proposed system can assist healthcare professionals in accurate and rapid diagnosis of skin diseases and has strong potential for real-time medical applications.

References

[1]. J. Ashwin, N. Ruthwick, T. Prabhakara, R. Vijaykumar, V. Vignesh, P. Nagaraj, Y. Manjunath, And D. Amit Gangadhyay, “Deep Long And Short Term Memory With Tunicate Swarm Algorithm For Skin Disease Detection And Classification,” Journal Of Electrical Systems, Vol. 20, No. 7s, Pp. 613–624, 2024.

[2]. A. Balasundaram, A. Shaik, B. R. Alroy, A. Singh, And S. J. Shivaprakash, “Genetic Algorithm Optimized Stacking Approach To Skin Disease Detection,” Ieee Access, Vol. 12, Pp. 88950–88967, 2024.

[3]. V. Arun Kumar, C. Chandana, G. Supraja, D. Haripriya, And E. Ravalika, “Sccnet: Skin Cancer Detection And Multi-Class Classification Using Deep Cnn Model With Estimated Disease Probabilities,” Sn Computer Science, Vol. 5, No. 733, 2024.

[4]. D. Kapoor, D. Gupta, Y. Gulzar, M. Alkanan, M. S. Mir, A. B. Soomro, M. Uppal, And R. Reshma, "Convolutional Neural Network-Based Multi-Classification Of Skin Disease With Fine-Tuned Resnet50 And Vgg16," The Open Bioinformatics Journal, Vol. 18, P. E18750362387304, 2025. Doi: 10.2174/0118750362387304250716055022.

[5]. M. Badiger, V. Kumara, S. C. N. Shetty, And S. Poojary, “Leaf And Skin Disease Detection Using Image Processing,” Global Transitions Proceedings, Vol. 3, No. 1, Pp. 272–278, 2022.

[6]. V. Pugazhenthi, S. K. Naik, A. D. Joshi, S. S. Manerkar, V. U. Nagvekar, K. P. Naik, And C. G. Palekar, “Skin Disease Detection And Classification,” International Journal Of Advanced Engineering Research And Science, Vol. 6, No. 5, Pp. 396–400, 2019.

[7]. Sun, Q., Huang, C., Chen, M., Xu, H., & Yang, Y. (2021). Skin Lesion Classification Using Additional Patient Information. Biomed Research International, 2021(1), 6673852.

[8]. Alenezi, Nawal Soliman Alkolifi. "A Method Of Skin Disease Detection Using Image Processing And Machine Learning." Procedia Computer Science 163 (2019): 85-92.

[9]. V.-D. Hoang, X.-T. Vo, K.-A. Phu, And K.-H. Jo, “Fusion Of Segmentation And Classification For Improving Skin Disease Diagnosis,” In Lecture Notes In Networks And Systems, Vol. 567, 2023, Pp. 144–154.

[10]. T. Gupta, V. Patial, D. Bali, S. Angaria, M. Sharma, And R. Chahota, “A Review: Lumpy Skin Disease And Its Emergence In India,” Tropical Animal Health And Production, Vol. 52, No. 6, Pp. 1–8, 2020.

[11]. M. Lin, Q. Chen, And S. Yan, "Network In Network," In Proc. Int. Conf. Learn. Represent. (Iclr), 2014.
[12]. K. Simonyan And A. Zisserman, "Very Deep Convolutional Networks For Large-Scale Image Recognition," In Proc. International Conference On Learning Representations (Iclr), 2015.
[13]. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, And L.-C. Chen, "Mobilenetv2: Inverted Residuals And Linear Bottlenecks," In Proc. Ieee/Cvf Conf. Comput. Vis. Pattern Recognit. (Cvpr), 2018, Pp. 4510–4520.
[14]. M. Gaikwad And A. Doke, "Comparative Analysis Of Statistical Optimizers For Logistic Regression," 2023 7th International Conference On Intelligent Computing And Control Systems (Iciccs), Madurai, India, 2023, Pp. 1193-1197, Doi: 10.1109/Iciccs56967.2023.10142817.
[15]. V. Nair And G. E. Hinton, "Rectified Linear Units Improve Restricted Boltzmann Machines," In Proc. 27th Int. Conf. Mach. Learn. (Icml), Haifa, Israel, 2010, Pp. 807–814.
[16]. A. Krizhevsky, I. Sutskever, And G. E. Hinton, "Imagenet Classification With Deep Convolutional Neural Networks," In Advances In Neural Information Processing Systems (Nips), 2012, Pp. 1097–1105.
[17]. C.-W. Hsu And C.-J. Lin, "A Comparison Of Methods For Multiclass Support Vector Machines," Ieee Trans. Neural Netw., Vol. 13, No. 2, Pp. 415–425, Mar. 2002.
[18]. M. Abadi Et Al., "Tensorflow: A System For Large-Scale Machine Learning," In Proc. 12th Usenix Symp. Operating Systems Design And Implementation (Osdi), Savannah, Ga, Usa, 2016, Pp. 265–283.
[19]. T. Fawcett, "An Introduction To Roc Analysis," Pattern Recognition Letters, Vol. 27, No. 8, Pp. 861–874, Jun. 2006.