Original Article

Skin Disease Classification Using Combined Machine Learning And Deep Learning Models

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DOI: 10.47750/pnr.2022.13.S09.406

Abstract

Skin disease is a very common disease of living organisms. In the medical world, tracking and classifying skin diseases is a complex process. Due to the complexity of individual skin tone and the near visible effect of infections, recognizing the exact type can sometimes be challenging. As a result, it is important to detect skin disease and identify it as soon as possible. Artificial intelligence (AI) is rapidly expanding into therapeutic areas in the modern environment For diagnostic purposes, more deep learning (DL) and machine learning (ML) methods are used. These techniques drastically improve the diagnostic process while also speeding it up. In this work, a combined deep learning (DL) and machine learning (ML) is developed to improve skin disease classification. The Convolution Neural Networks mode is used for feature extraction and classified using Machine Learning models include Decision Tree, Nearest Neighbor, Support Vector Machines and Light Gradient Boosting classifier. To identify the best predictive model, a comparative study was carried and the hybrid method CNN with SVM gives the optimum results of 91.04% accuracy.

Keywords — Decision Tree, Knearest Neighbor, Support Vector Machine, and Light Gradient Boosting Machine.

Introduction

The epidermis is the most important organ of the human body covering an area of 21 to 23 square feet. It protects many important organs of the human body from external harm and pathogens and the weather, helps in thermoregulation, and activates sensation, heat and cold sensations. However, the skin can be altered by external and genetic variables. In human population, skin diseases are very common. Three types of skin problems often affect human skin. 1) infectious skin disorder, 2) bacterial skin disorder, and 3) contact dermatitis disorder. A skin condition may change the consistency or color of the skin. Skin diseases are persistent, contagious and in some cases can lead to skin cancer. Fungal and allergic disorders can be easily treated if they are adequately diagnosed and identified in their early stages. However, in case of viral diseases, it is necessary to identify them immediately. AI models, ML [1,2] and DL techniques [3,4] have advanced rapidly in the clinical field in the last few years. Numerous ensemble-based [5] machine learning approaches and artificial neural network-based approaches [6] have been widely used to improve skin disease predictions. Computer vision, in addition to physical symptoms, is important in diagnosing many skin diseases. A computer vision approach helps diagnose skin diseases with greater accuracy.

A fusion of ML and DL models is constructed in this study to classify skin diseases. For classification models, four ML models were used including Decision Tree, Nearest Neighbor, Support Vector Machines and Light Gradient Boosting Classifier. For feature extraction, convolutional neural networks were used. Finally, a series of tests were performed to select the best predictive models.

Literature Review

Skin diseases are more common than other types of diseases. A fungal infection, bacteria, viruses or allergies, along with other factors, can cause skin problems. Changes in the surface or tone of the skin can be caused by skin disease. Skin infections are chronic, contagious and in some cases can lead to skin cancer. Consequently, skin diseases should always be detected early to prevent their evolution and spread. Diagnosing and treating skin disease takes a long time, and it costs the patient both financially and physically. Many researchers have analyzed images of skin conditions in an attempt to establish a mechanism for diagnosing various skin diseases. In this section, various dermatological diagnostic techniques are explored, Khan et al. [7] developed an SLC architecture with a fast region-based CNN for lesion ROI localization, an iteration-controlled Newton-Raphson approach for feature extraction. DenseNet-201 was used to extract deep features. Finally, the authors used a multilayer perceptron as a classifier. Almaraz-Damian et al. [12] offered a pipeline, integrating pre-processing, feature extraction, feature fusion, and classification. The disease ROIs were extracted by the authors as a pre-processing step, followed by an intensity scaling process. CNN extracted several custom features based on mutual information measurement, including features and shape, color, and texture features. Several classification methods such as linear regression (LR), SVM and relation vector machines (RVMs) were used to classify the ROIs. In (Govindasamy et al., 2020), the authors used a CNN to predict physician vision, where they focused on comparing hand-crafted features and a CNN-feature extraction tool, additionally analyzing the impact of feature extraction and fully connected layers. An end-to-end CNN model. The authors used VGG16 as the feature extraction tool, K-nearest neighbors and a random forest (RF) as the classifier. CNN features extraction showed significant improvement over hand-crafted features with high-level features from the last convolutional layer of CNN, and the power of CNN comes from feature extraction rather than fully connected layers. Depending on the application, it is replaced by another classifier. To recognize Synthetic Aperture Radar (SAR) images, (Wang et al., 2019) authors suggested combining CNN and Extreme Learning Machine (ELM) algorithms. Variation in complex feature extraction of images, regardless of any shape distortion of the image, and ELM as a recognitionThe experimental result shows that the algorithm can alleviate the overfitting problem, speed up the convergence of the network and reduce the testing time. The authors in (Basly et al., 2020) applied a CNN ResNet framework, coupled with an SVM classifier, for task of recognizing human activity and obtained better classification. An image classification approach based on CNN and SVM was presented by the authors in (Mu and Qiao, 2019 By using CNN to pre-process the original images, they were able to identify important features and remove unnecessary ones. The extracted features are injected into an improved SVM model and evaluated on a composite image set taken from the Caltech Image Archive. Experimental results demonstrate the effectiveness of CNN feature extraction by SVM classifier.

Materials and Method

Image Dataset

The dataset plays a crucial role in the training of our proposed Machine Learning Techniques for automated diagnosis. The dataset named HAM10000 is the skin disease dataset that has been extracted from the Kaggle, which has served as a benchmark database downloaded from the source [76]. The dataset comes in metadata format such as comma-separated values file (.CSV), consisting of age, gender, and cell type. The dataset also provides additional tips and tricks to overcome certain challenges such as overfitting and limited data, which will help in increasing the model's accuracy and performance. In this dataset, we have seven different types of skin problems in our dataset, namely Melanocytic Nevi (NV), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), Vascular Lesions (VASC), Actinic Keratoses, and Intraepithelial Carcinoma (AKIEC), Basal Cell Carcinoma (BCC), and Melanoma (MEL). Totally 10,015 images obtained from HAM10000 dataset each class size is Nv-6705, Mel-1113, Bkl-1099, Bcc-514, Akiec-327, Vasc-142, Df-115. Out of these 80% (8011) images were used for training, 20%(2004) images were used for testing. There is an imbalance in the number of skin images in each type of lesion present in the dataset. To avoid this imbalance, we performed data augmentation techniques to balance all types of lesions to the same range of images. The dataset is divided into two parts: training data, testing data of 80%, and 20%, respectively, to enhance our model's generalization. The model is evaluated against the ground facts that are associated with the training dataset. The target size of the images for our proposed model is 224 × 224. This research aims to determine the accuracy in diagnosing skin disease on dermatoscopic images using our proposed approach.

Proposed Methodology

Artificial intelligence refers to the imitation of human brain functions by computers, specifically computer systems. DL [17,18] and ML models are used in practice to solve real-world problems. In this work, a hybrid of DL and ML models is proposed to handle the skin disease classification problem. Deep learning model CNN used to extract features from the data samples for this work, and classified using machine learning methods performance metrics were used to evaluate the input model. The work how diagnose of the proposed model is given in Fig 1.

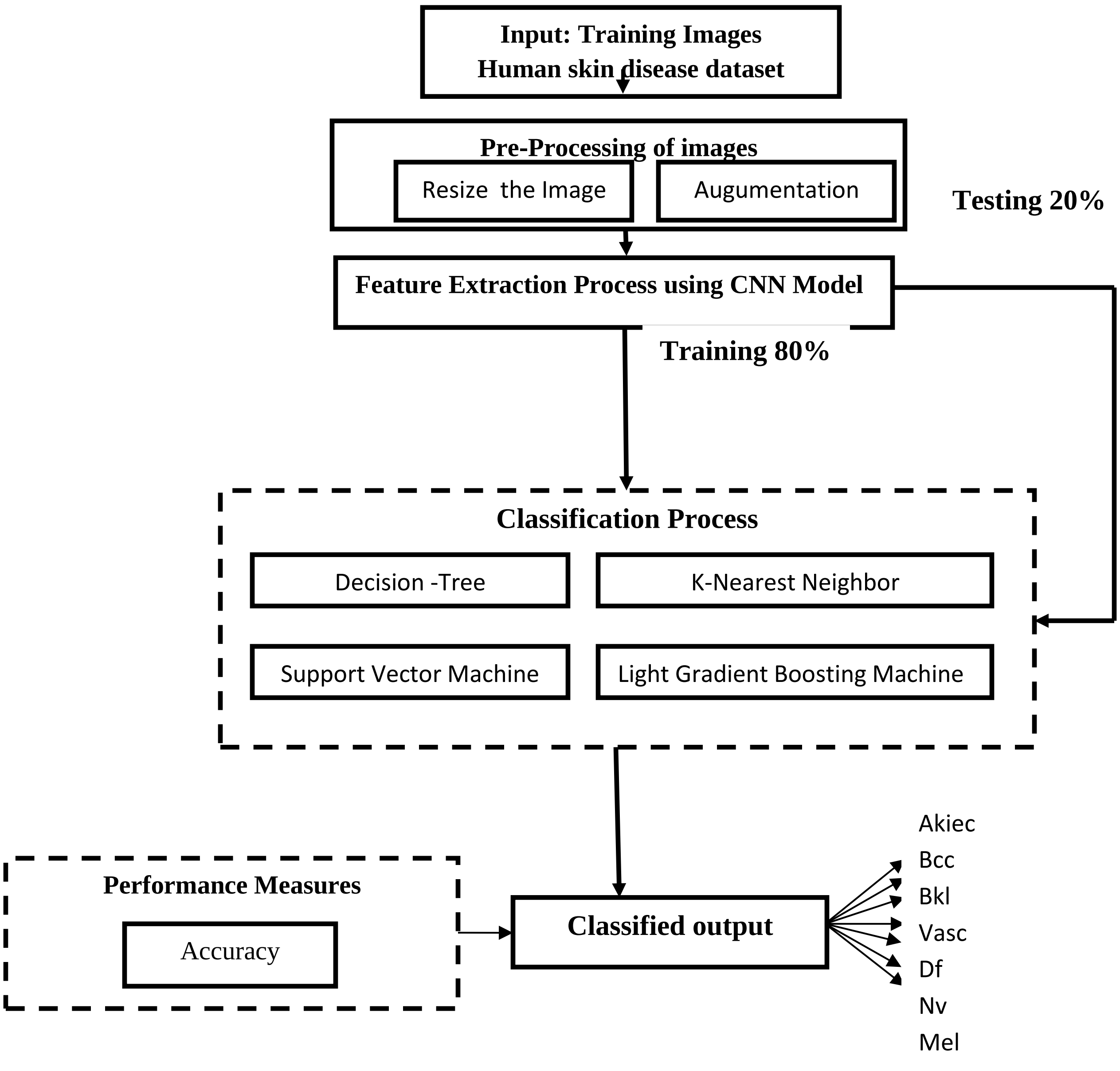

Fig.1 Overall working process of Proposed Method

Features Extraction using CNN

Convolution layers are used to extract the features from input training samples. Each convolution layer has a set of filters that helps in feature extraction. The first convolution layer captures simple features while the last convolution layer captures complex features of training samples. Features are extracted by taking the convolution of portion of data sample. The amount of data portion that the filter traverses each time is proportional to the stride length and padding value. The convolution output is then passed through an activation unit called ReLU(Rectified Linear Unit). This unit converts the data into its non-linear form. The output of ReLU is clipped to zero only if convolution output is negative. The output of ReLU is then passed through a pooling layer. Pooling layer remove any redundant features that's captured during convolution. Thus this layer reduces the size of data sample. In gene ral , size of input image is reduced by half with help of a 2x2 filter. This process of passing data through convolution and pooling layer successively is repeated as per the design of CNN model. The output from successive convolution and pooling layer is then passed through a multi-layer neural network. Each unit acts as feature map that carries information about a unit.

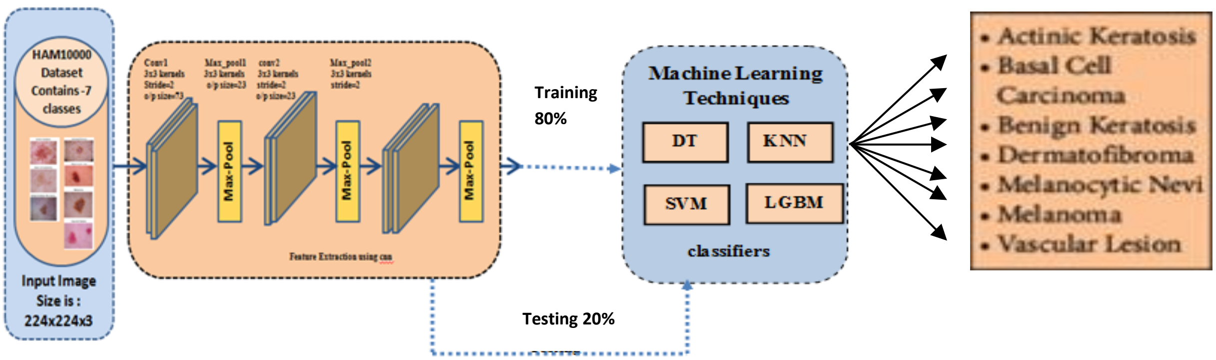

Fig. 2 Work flow of skin disease classification using CNN

Machine Learning Models for Classification

The purpose of classification using Machine Learning models is to approximate the transformation matrix from categorical input variables to categorical output variables. The basic goal of classification is to establish under which class new information falls. The following are the Machine Learning classifiers used in proposed work. Machine Learning uses two types of techniques supervised and unsupervised Machine Learning. Supervised learning , which trains a model on known input data and output data, so that it can predict feature outputs. The Unsupervised learning which hidden patteren in input data.

a) Decision Tree

This algorithm belongs to the supervised learning algorithm. The objective of this technique is to learn some basic decision rules from the training data to build a learning model that correctly predicts the classified variable. In decision trees, predicting the class label for a record starts at the root of the tree. The elements of the source attribute are then compared to the values of the label attribute. Each branch of the tree is associated with that value and moves to the next node based on the correlation.

b) Knearest Neighbor(KNN)

Nearest neighbor classification is one of the easiest classification techniques in image space. Therefore, when considering a test image, the label of the closest point in the learning set is assigned according to the intervals in the image. By default, in KNN, the Euclidean distance metric is used to calculate the distance between multiple data points in an image, and each pixel is assigned a distance. The Euclidean distance between two pixels is referred to as 'distance'.

c) Support Vector Machine(SVM)

It belongs to the category of supervised learning, a prominent algorithm [26]. This approach is used in both classification and regression analysis. The whole purpose of this method is to separate the target classes with the largest possible difference using a hyperplane. This algorithm is used as a multi-class classification model in this investigation.

d) Light Gradient Boosting Machine(LGBM)

The LGBM algorithm is used to determine and create a data model. "The LGBM algorithm depends on the decision tree algorithm, which splits tree leaf-wise with the best match, whereas other Boost algorithms split tree depth-wise or leaf-wise" where, leaf is considered as a category. Data and its branches are considered as its subgroups. Therefore, when generating a leaf in a well-lit GBM, the leaf-wise algorithm will be more accurate and bring improved precision, which can be used to obtain efficient information using any of the currently available optimization algorithms. Also, it is the fastest, followed by 'light'[10]. LGBM is a variant of GBM that is designed to be distributed and efficient with the following advantages: faster training speed and higher performance, lower memory usage, better accuracy, parallel and GPU learning support, and ability to handle big data (Gupta& Sedamkar,.2020).

Experimental Results and Discussions

Totally 10,015 images obtained from HAM10000 dataset were trained in this CNN model where Nv-6705, Mel-1113, Bkl-1099, Bcc-514, Akiec-327, Vasc-142, Df-115. Out of these 70% (7011), images were used for training, 20%(2003) images were used for validation and the remaining 10%(1001) were used for testing. The skin disease prediction networks output layer identifies seven classes: “Akiec”, “Bcc”, “Bkl”, “Nv”, “Df”, “Vasc” and “Mel”. The parameters of the proposed CNN network id tabulated in table 1.

Images are first rescaled to 224 × 224 is fed to the network. All three color channels are processed directly by the network. The three subsequent convolutional layers are then defined as follows.

- Image size of 224 x 224 and 32 filters with size of 3 x 3 are applied to the input in the first convolutional layer, followed by a rectified linear operator (ReLU), a max pooling layer taking the maximal value of 2 × 2 regions with two-pixel strides and a local response normalization layer.
- The 112 × 112 output of the previous layer is then processed by the second convolutional layer, containing 64 filters of size 3 x 3 pixels. Again, this is followed by ReLU, a max pooling layer and a local response normalization layer with the same hyper parameters as before.

Finally, the third and last convolutional layer operates on the 54 × 54 by applying a set of 64 filters of size 64 × 3 × 3 pixels, followed by ReLU and a max pooling layer. The features extracted from the convolution base is given as input to the Machine Learning Techniques and Performance of these models has been evaluated and compared by using accuracy values. Table I explain parameter of cnn model, and Table II are overall calculated accuracy for

performance measures.

Parameter	**Description**
Input Size	224x224
Colour channels Filter size	3(RGB) 3x3
Activation function Pooling layer	Rectification Linear Unit(ReLU) Max Pooling

Max pooling size	2x2
Stride	2
Final layer	Softmax(seven class)
Dropout	0.5
Total number of layers	12
Total trainable parameters	1,23,583

Table I. Parameters for CNN model

The below bar-diagram Fig. 3 represents the number of correctly predicted images in each class, with a maximum value of correctly predicted CNN+SVM with an accuracy of 91.04%.

Table II. Overall Performance Analysis using CNN with Machine Learning Models

Hybrid Classification models	**Overall calculated Accuracy (%)**
CNN+DT	85.75
CNN+KNN	81.69
CNN+SVM	**91.04**
CNN+LGBM	84.37

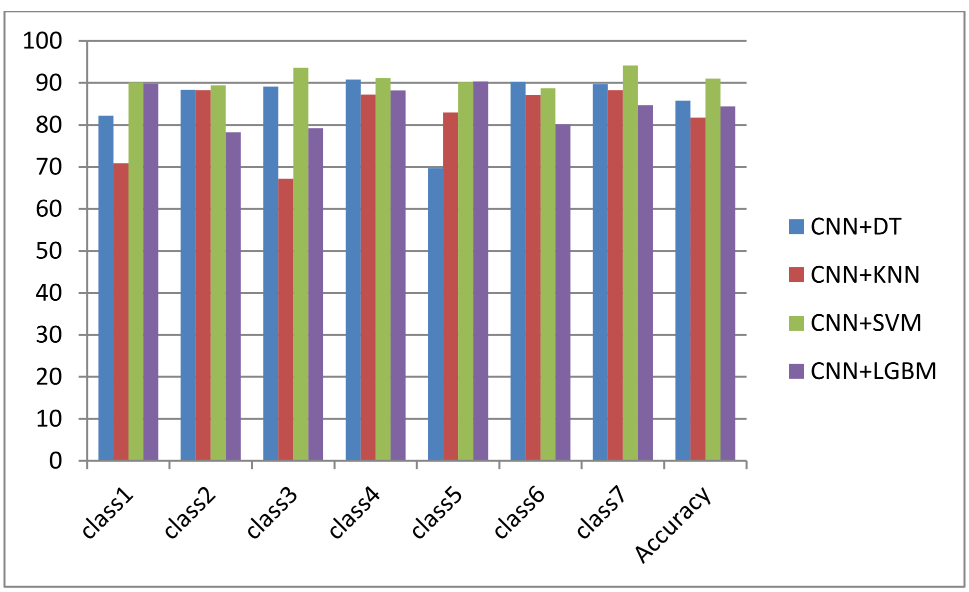

Fig. 3 Performance Analysis of Each Class using CNN with Machine Learning Model

In this work, a system for automatic classification of skin diseases was developed. Data from the HAM10000 was used for this analysis. In this study, the diagnostic procedure was carried out using a combination of ML models and Convolutional neural network. While ML models were used to identify disease categories, deep learning models were used to extract properties from the raw images. The Convolutional Neural Network deep learning model and four different machine learning models are both examined in this study. The feature extraction with multiple classifier models is the main focus of this work. As feature extraction methods Convolutional neural networks, as well as DT, KNN, SVM, and LGBM algorithms, were employed for classification techniques. Every possible combination is tested, and performance is evaluated according to accuracy. CNN+SVM has been found to be the best classifier model, in the end. Even when a Convolutional Neural Network is utilized as a model for feature extraction, this model outperforms it. Tables II and offer the performance justification for all the combinations.

This combination (CNN+ SVM) outperforms all other classifiers in terms of performance. The above combination was found to have the precision with 89.83% for each disease class. Fig. 3 further shows that the fusion technique of CNN with SVM gives the overall highest accuracy of 91.04%.

Conclusion

The largest natural component of a human being is the epidermis. Skin conditions can develop as a result of many internal and external factors. Therefore, diagnosis of skin diseases is an important part of medical science. Because it can reduce the number of people who die from contact with skin conditions or infectious diseases. The treatment strategy is time-consuming and the disease cannot always be correctly identified. Automated classification of skin diseases can be very helpful in these situations. In this study, an electronic method for diagnosing skin diseases is suggested. For this technique, a combination of ML and DL models was used. One deep learning model for feature extraction from training data was integrated with four well-known machine learning classifiers in the proposed approach. After detailed comparison, it was found that the Convolutional Neural network model CNN with Support Vector Machine Classifier provides the most accurate predictions, with an accuracy rate of 91.04%.

REFERENCES

[1] T. Shanthi, R.s Sabeenian, R. Anand Automatic diagnosis of skin diseases using convolution neural Network. Microprocessors and Microsystems, volume 76, july 2020, 103074

[2] N. Rajkumar, R. Sugumar, K. V. Daya Sagar, Skin Diseases Classification Using Hybrid AI based Localization Approach, Computational Intelligence and Neuroscience, Volume 2022 | Article ID 6138490 | https://doi.org/10.1155/2022/6138490.

[3] Md. Al Mamun, Mohammad Shorif Uddin, Hybrid Methodologies for Segmentation and Classification of Skin Diseases: A Study, Journal of Computer and Communications ,Vol.9 No.4, April 2021 .

[4] S. Kusuma; G. Vasundharadevi; D. M. Abhinay Kanth, A Hybrid Model for Skin Disease Classification using Transfer Learning, 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT), Publisher: IEEE.

[5] Md. Kamrulhasan Md. Toufick E.Elahi, dermoexpert: Skin Lesion Classification using a
Hybrid Conolutional Neural Network Through Segmentation, Transfer Learning, andAugmentation, Informatics in Medicine Unlocked Volume 28, 2022, 100819.

[6] Parvathaneni Naga Srinivasu, Jalluri Gnana SivaSai, Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM, National Library of Medicine 2021 Apr 18. DOI: 10.3390/s21082852
.[7] Emine Cengil1, Muhammed Yıldırım, Ahmet Çınar, Hybrid Convolutional Neural Network Architectures for Skin Cancer Classification. (1st International Conference on Applied Engineering and Natural Sciences ICAENS 2021, November 1-3, 2021) (DOI: 10.31590/ejosat.1010266).

[8] Jorge Alexander Ángeles Rojas , Hugo D. Calderón Vilca, Ernesto N. Tumi Figueroa, Hybrid Model of Convolutional Neural Network and Support Vector Machine to Classify Basal Cell Carcinoma, vol.25 no.1 , Epub 13-Sep-2021 https://doi.org/10.13053/cys-25-1-3431.

[9] Sella Veluswami, Jansi Rani; Ezhil Prasanth,Melanoma Skin Cancer Recognition and Classification Using Deep Hybrid Learning, Journal of Medical Imaging and Health Informatics, Volume 11, Number 12, December 2021, pp. 3110-3116(7). DOI: https://doi.org/10.1166/jmihi.2021.3898.

[10] Nisreen I. Abo Dabowsa, N. Amaitik, A hybrid intelligent system for skin disease diagnosis, 2017 International Conference on Engineering and Technology (ICET), DOI:10.1109/ICENGTECHNOL.2017.8308157

[11] Aman Shakya Mr. Anuj Kumar, Dharamveer Sing A Melanoma Skin Cancer Diagnosis Using Hybrid Feature-Optimized MSVM Classification Model On Dermotoscopic Images Sensors. 21(8) (2021) 2852.

[12] Banasode, P., Patil, M., & Ammanagi, N. A Melanoma Skin Cancer Detection Using Machine Learning Technique: Support Vector Machine. IOP Conference Series: Materials Science and Engineering. 1065(1) (2021) 0–5.

[13] Kadampur, M. A., & Al Riyaee, S. X. Skin cancer detection: Applying a deep learning-based model-driven architecture in the cloud for classifying dermal cell images. Informatics in Medicine Unlocked, 18(December 2019) (2021) 100282.

[14] Hasan, M., Barman, S. Das, Islam, S., & Reza, A. W. Skin cancer detection using convolutional neural network. ACM International Conference Proceeding Series: March 2020 (2019) 254–258.

[15] Ravindar Reddy Baireddy, R. Nagaraja, A hybrid particle swarm optimization with multi-objective clustering for dermatologic diseases diagnosis, Journal of Intelligent systems, DOI: https://doi.org/10.1515/jisys-2022-0028.

[16] Pravin R. Kshirsagar , Hariprasath Manoharan , S. Shitharth , Deep Learning Approaches for Prognosis of Automated Skin Disease International Journal of Engineering Trends and Technology. MDPI, Basel, Switzerland, 2022.

[17] V. Vidya Lakshmi, and J. S. Leena Jasmine, A Hybrid Artificial Intelligence Model for Skin Cancer Diagnosis, Computer Systems Science & Engineering, DOI:10.32604/csse.2021.015700

[18] Md. Mahbubur Rahman, Mostofa Kamal Nasir , Md. Nur-A-Alam, Hybrid Feature Fusion and Machine Learning Approaches for Melanoma Skin Cancer Detection, 18 January 2022

[19] Kaushik, A. Understanding ResNet50 architecture. OpenGenus IQ: Computing Expertise & Legacy (2020).

[20] Manasa, K., & Student, M. T Skin Cancer Detection Using VGG-16. European Journal of Molecular & Clinical Medicine 08(01) (2021) 1419–1426.

[21] Waseem, M. How To Implement Classification In Machine Learning? Edureka (2021).

[22] Team, E. What is the Definition of Machine Learning? Expert.Ai (2021)

[23] Ray, S. SVM | Support Vector Machine Algorithm in Machine Learning. Analytics Vidhya (2021).

[24] Great Learning Team. The Ultimate Guide to AdaBoost Algorithm | What is AdaBoost Algorithm? GreatLearning Blog: Free Resources What Matters to Shape Your Career! (2021).

[25] Narayanan A G, H., Singh, Dr J.A.P. Skin Disease Ensemble Classification Using Transfer Learning and Voting Classifier. International Journal of Engineering Trends and Technology. 69(12) (2021) 287-293.

[26] Saini, A. Decision Tree Algorithm - A Complete Guide. Analytics Vidhya (2021).