A Convolutional Neural Network Based Prediction Model for Classification of Skin Cancer Images

Vanshika Saini[1(✉)], Neelanjana Rai[1], Nonita Sharma[2], and Virendra Kumar Shrivastava[3]

[1] Electronics and Communication Engineering (AI) Department, Indira Gandhi Delhi Technical University for Women, Delhi, India
{vanshika083bteceai21,neelanjana100bteceai21}@igdtuw.ac.in
[2] Information Technology Department, Indira Gandhi Delhi Technical University for Women, Delhi, India
nonitasharma@igdtuw.ac.in
[3] Department of Computer Science and Engineering, Alliance College of Engineering and Design, Alliance University, Bangalore 562106, India

Abstract. There has been an unprecedented rise in the cases of skin diseases since past few decades owing to several factors. Among several skin diseases, skin cancer has also taken a steep rise and resultantly it becomes imperative to devise an efficient model to detect skin cancer. The requirement for automatic detection of skin cancer further grows owing to rise in rate of melanoma skin cancer, its expensive treatment, and its high fatality rate. Treatment of cancer cells frequently necessitates patience and manual inspection. Here, in this work authors propose an image processing and machine learning approach for skin cancer detection. It also uses a feature extraction technique to retrieve the features of the injured skin cells. The proposed model uses convolutional neural network classifier to stratify the extracted data. During the experimental evaluation, it is observed that the proposed system yields an accuracy of 77.03% and a training accuracy of 80% for the datasets available in public domain.

Keywords: Melanoma · Diagnostic Accuracy · Framework · Data analysis · Validation approach · Datasets · Confusion matrix · Accuracy table · ML algorithms

1 Introduction

Skin in Cancer is a type of sickness triggered with the aid of the extraordinary boom of the skin cells which takes place due to the changes in the houses of ordinary pores and skin cells [1]. Most often it happens to the pores and skin uncovered to the sun. There are three principal sorts of pores and skin cancer – squamous cell carcinoma, basal cell carcinoma and Melanoma [2]. The deadliest kind is Melanoma. This happens

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due to the ordinary mutations in the DNA of the skin cells which motives them to boom uncontrollably and structure a mass of Cancer cells. One of the foremost reasons of skin most cancers is UV mild exposure [3]. UV rays harm the skin cells and causes overgrowth of cells which strengthen skin cancer. The healing process, appropriate drug administration, and avoidance of the worst skin cancer symptoms can all be helped by early detection and accurate diagnosis of the disease [4]. Therefore, a system for early diagnosis that can lower the risk factor for people as well as facilitate the importance to increase public awareness of various forms of skin cancer and other skin issues.

A modification of the Multilayer Perceptron (MLP), the Convolutional Neural Network (CNN) is made specifically to process two-dimensional data. Given its extensive use with picture data and high network depth, CNN is categorized as a deep neural network. CNN's design is similar to that of neural networks in general, and its neurons have the functions of weight, bias, and activation. The CNN architecture consists of the fully connected layer with softmax activation as the classification layer, the convolution layer with ReLU activation as the feature extraction layer, and the pooling layer as the feature extraction layer [4].

In the proposed model, authors have used CNN because it provides great image processing accuracy. Dermatologists input all their information into the primary layer, which serves as the input layer. The next layers then convey the information to the pooling layer after it has been created by the input layer and given to them.

The pooling layer uses a max pool or a min pool to pool the information structure. From the pooling layer, the data is passed to the straightening layer for smoothing, which turns the information into a one-dimensional vector. At that time, the information is dense enough to be shifted over to the category they desire, whether it be for a benign or malignant circumstance [5]. The automatic skin cancer detection method used in this paper uses convolutional neural networks to categorize cancer images as either benign or malignant melanoma [6].

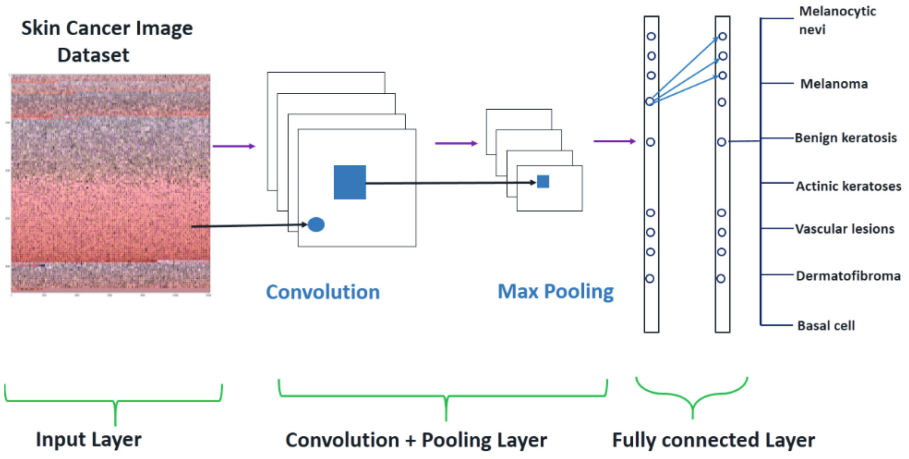

Fig. 1. Model building and evaluation

The manuscript is divided into several sections. First section emphasizes on the introduction of the research work; second section demonstrates the related work done in this area. Third section emphasizes on the methodology. Fourth section presents the results and a complete discussion of the same. After that the manuscript is concluded along with the future scope (Fig. 1).

2 Related Work

Once the type of skin cancer has been determined, it can be treated by having it surgically removed as soon as is practical. Early detection is vital in the treatment of skin cancer. However, the prognosis is typically dismal for more serious cases. It's important to prevent misdiagnosing basal cell carcinoma as being fatal in nursing medicine. According to a survey conducted by B and W Hospital, 75% of participants claimed that employing AI for diagnosing has helped them because the results are quicker and much more accurate [7]. Human inaccuracy can occasionally lead to a false alert about the detection of skin cancer, raising patient anxiety levels. On the other hand, failing to find skin cancer in a patient frequently leads to a failed recovery [8].

Anita et al. demonstrated the use of CNN for classification of the skin cancer images and compared the accuracy of 13 different models on various performance metrics and concluded that CNN models perform well in the classification of skin cancer. Authors here stated that the model can be employed for prediction purpose [9].

Further, Keefe et al. also employed CNN for classifying the images of skin cancer. Authors here employed the model on a dataset consisting of more than 10,000 images of seven categories of skin lesions. They further classified the lesions as cancerous and non-cancerous. The research work concluded that deep learning modes can be employed for prediction and early diagnosis of the disease which could help in preventing the disease [10, 11].

Furthermore, Garg et al. characterized dermoscopy images using CNN. The deep learning model was evaluated based on precision and recall. The model was optimized on the basis of few data augmentation techniques and transfer learning methods. The model achieved an accuracy of 88%, which was enhanced to 90.51% using transfer learning [12]. Additionally, Saba et al. deliberated that deep learning-based prediction requires expert analysis and hence its very lengthy and expensive process. Here, authors suggested a novel automated approach for skin lesion and classification based on CNN. The model outperformed existing models with enhanced accuracy and precision [13].

Authors have identified that several researchers are working on deploying the deep learning network to classify skin cancer images [14, 15]. The models have performed accurately but there is a dire need to perform the exploratory analysis along with model. Authors in this research work performed EDA and then deployed CNN on the dataset. Afterwards, accuracy is compared.

3 Methodology

The following section demonstrates the step-by-step methodology of the research work presented in the manuscript. The detailed flowchart is shown in Fig. 2. Here various steps are demonstrated along with the flow of various activities. Various steps are elaborated as under:

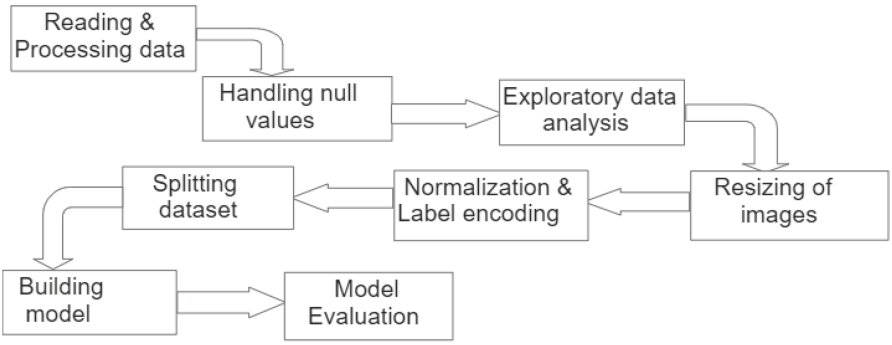

Fig. 2. Flow Chart for proposed methodology

3.1 Reading and Processing Data

The first step involves the gathering of data. The data is in the form of images. The authors created the image path dictionary in this phase by merging the jpg-formatted photos from both folders and the base directory base skin dir. Also, authors imported the crucial libraries needed for the following steps in this stage. Authors have read the csv file in this phase by joining the base folder, or base skin dir, where all the photos are stored. After that, we created a few new, readily understood columns for future use, containing column path, which has the picture id, column cell type, which contains the lesion type's brief name, and column cell type idx, which assigns a code between 0 and 6 to the lesion kind. After collecting the data, the data is preprocessed to get its cleaner form. Here, In this step, authors examine each field's datatype and any missing values [16].

3.2 Exploratory Data Analysis

EDA is the process through which authors examine various dataset characteristics, including their distributions and actual counts [17]. Figures 3, 4, 5 and 6 demonstrates the results of EDA in the form of various graphs. Figure 3 shows the plot of distribution of localization field. Triston has the highest distribution upto 50,000 cases. Figure 4 demonstrates that the back, lower extremities, trunk, and upper extremities are severely compromised skin cancer regions. Further, EDA is done on the basis of Age group, which shows that the skin cancer patients between the ages of 30 and 60 are more common. Lastly, in Fig. 6, the distribution of skin cancer patients among male and female is demonstrated which shows that the number of cases are higher in male than females.

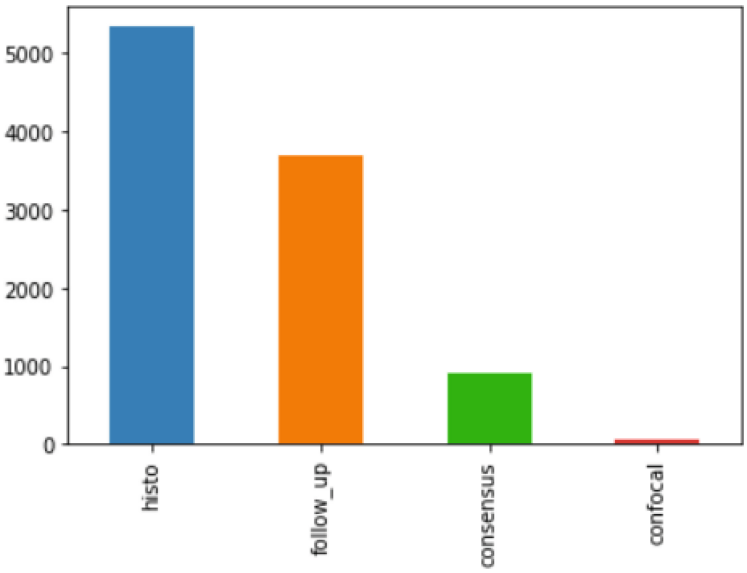

Fig. 3. Plotting the distribution of localization field

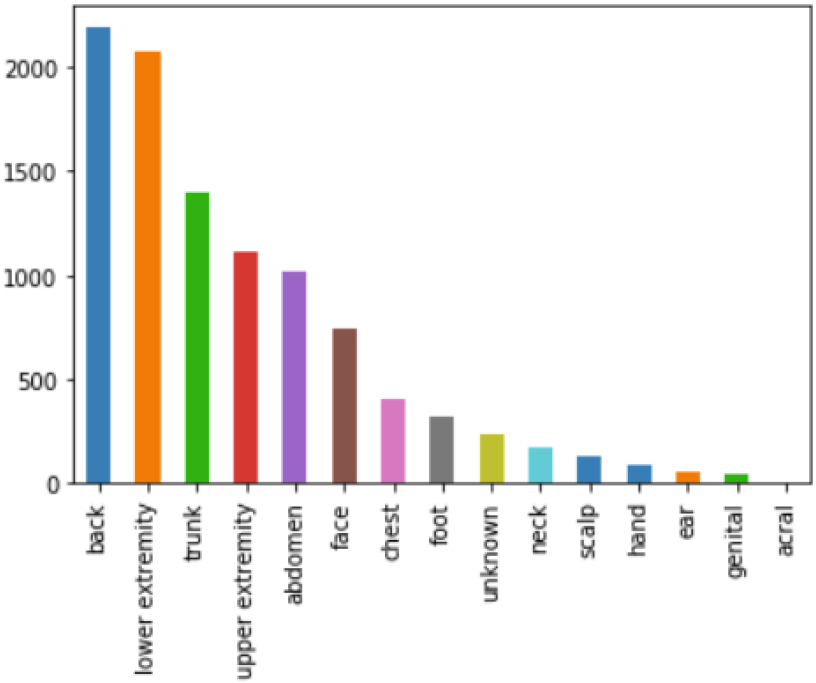

Fig. 4. Plot for skin cancer regions vs. Frequency.

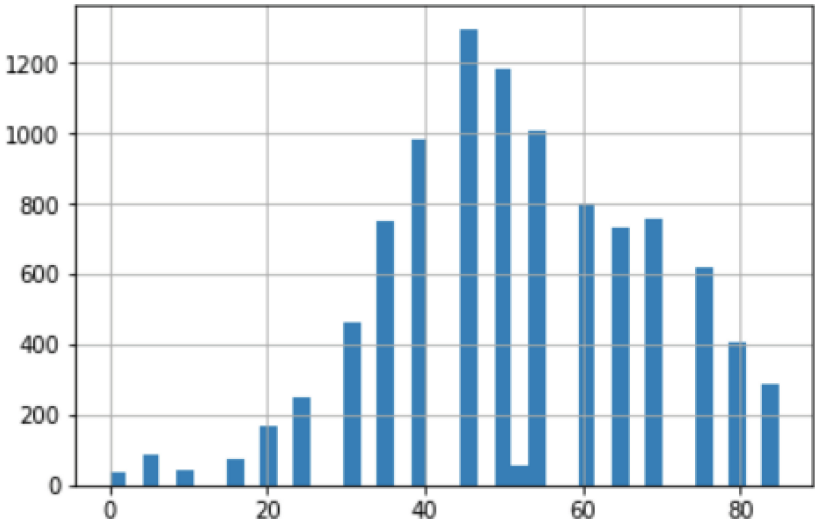

Fig. 5. Plot for age vs. skin cancer cases

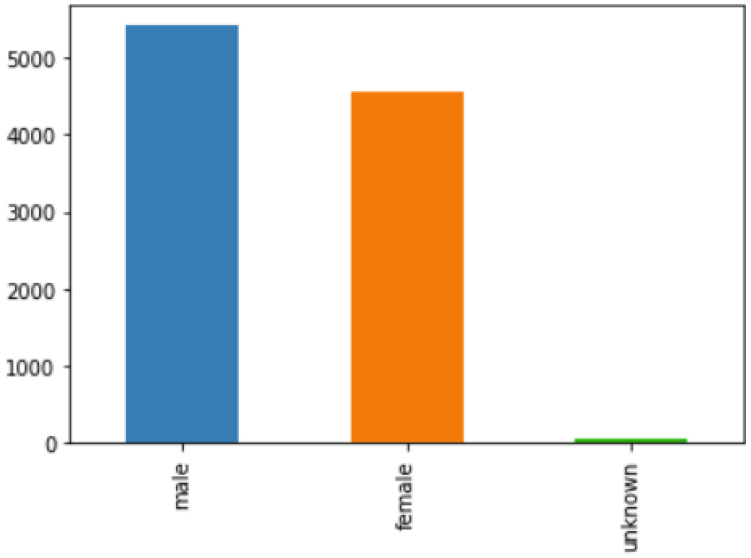

Fig. 6. Plot for gender vs. skin cancer cases.

3.3 Resizing of Images

In this stage, images will be loaded from the image path in the image folder into the column labelled image. We also resize the photos because TensorFlow cannot manage their original dimensions of 450 × 600 × 3, so we change their size to 100 × 75. Be patient; it will take some time since this step involves resizing all 10015 photos to 100 × 75 (Fig. 7).

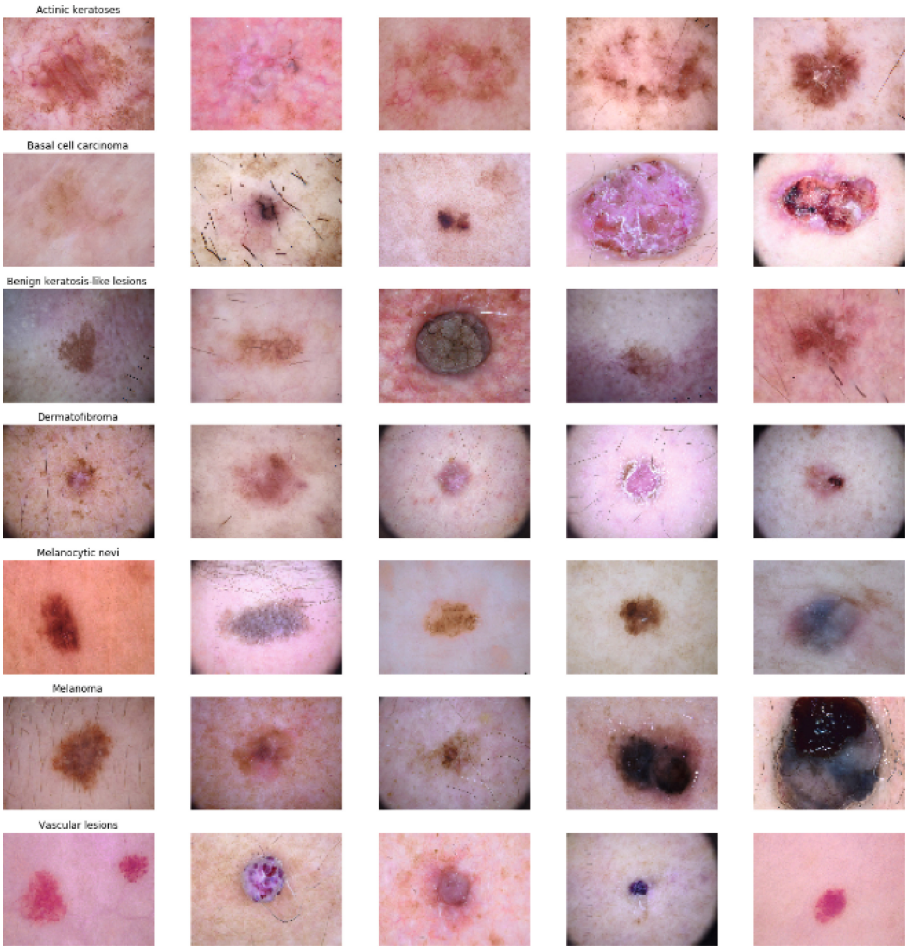

Fig. 7. Resized images

3.4 Normalization and Label Encoding

The next step involves the process of normalization, which is scaling the images to a similar form so that proper training of the model could be done. Label Encoding is done to convert the data into numerical form by assigning various numbers to various classes.

3.5 Splitting the Dataset

The dataset was divided into a training and testing set with an 80:20 ratio in this stage.

Further by eliminating from the x train and x test average readings and dividing by its standard deviation, the data has been normalized. The seven grades of skin cancer types on the labels range in severity from zero to six. Now these labels should be converted as one hot vector. After label encoding authors have split the data into ratio of 80:20 for training and testing the model.

3.6 Building the Model

The next step is to build the model. The convolutional (Conv2D) layer is the initial layer. It resembles a group of customizable filters. For the first two conv2D layers, I opted to use 32 filters, and the final two, 64 filters. Each filter deploys the kernel filter to a specific region of the picture that is defined by the kernel size. The entire image is exposed to the kernel filter matrix. These filters can be viewed as a picture alteration.

CNN can enhance the image's global properties by combining local features by combining convolutional and pooling layers and from these altered images CNN can identify features that are valuable everywhere (feature maps). The pooling (MaxPool2D) layer of CNN is the second crucial layer. Simply put, this layer works as a down-sampling filter. It selects the maximum value after examining the two adjacent pixels. These are applied to reduce computational expense and, to a smaller degree, to lessen overfitting. The size of the area that needs to be pooled must be chosen; the more significant the down-sampling the higher the pooling dimension.

Dropout is a regularization technique in which, for each training sample, a portion of the layer's nodes are arbitrarily ignored (having their weights set to zero). As a result, a portion of the network is randomly dropped forcing the network to pick up traits in a scattered fashion. Furthermore, this method enhances generalization The network is given nonlinearity by using rectifier activation function here the used rectifier is relu. The final images are transformed into a single 1D vector using the flatten layer. In order to employ fully connected layers after several convolutional/maxpool layers, this flattening step is required. It incorporates every local feature discovered in the earlier convolutional layers.

3.7 Model Evaluation

After model building the next stage entails reviewing our model's testing and validation accuracy, plotting a confusion matrix, and counting the number of misclassified images for each kind of the cancer.

4 Results and Discussion

We gained a thorough understanding from the dataset's exploratory data analysis. We can deduce that Melanoma cells predominately cover Melanocytic nevi cells from the distribution of different cell types. After plotting the graph showing where the cancer cells were located in each part of the body, we deduced that the majority of them were located on the back, trailed by the lower body. Next Most patients are between the ages of 30 and 60, according to the graph we used to determine the age group of patients. Next, we deduce that there are more cases of skin cancer in men than women when we plot the graph to compare cases between men and women. The distribution of skin cancer types in different age groups is then compared, and we conclude that type six skin cancer is prevalent in all age categories.

In our machine learning model our algorithm appears to have rendered the most erroneous predictions for basal cell carcinoma, (coded as 3), trailed by vascular lesions

(coded as 5), and melanocytic nevi (coded as 0) while actinic keratosis (coded as 4) has generated the fewest errors. Which is also represented by the confusion matrix Confusion matrices exhibit counts among expected and observed values. The output "TN" stands for True Negative and displays the number of negatively classed cases that were correctly identified. We can easily increase our model's accuracy further such that it exceeds above 80% (Figs. 8 and 9).

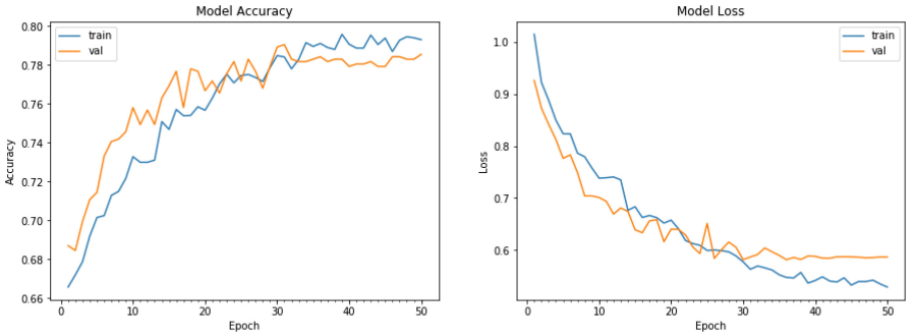

Fig. 8. Plot of model accuracy

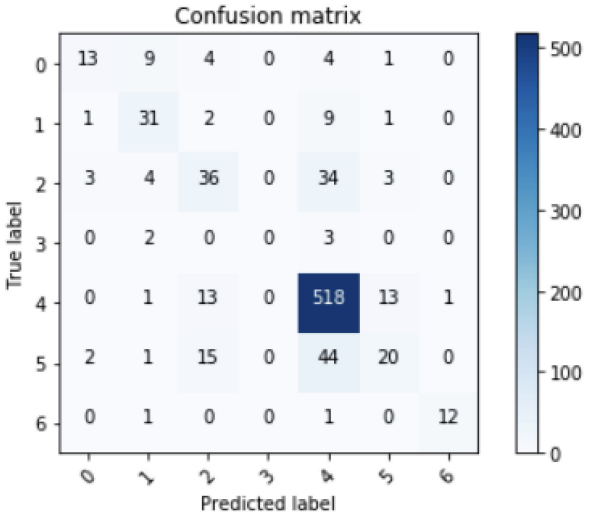

Fig. 9. Confusion matrix for actual and predicted categories

5 Conclusion

In this research paper, the convolutional neural network-based method for classifying melanoma has been developed. A technology is being developed that can assist patients and medical professionals in detecting whether a skin cancer is benign or malignant.

According to the experimental and assessment part, the model can be used as a standard for supporting medical practitioners in the early detection of skin cancer. Any doctor can obtain accurate results by obtaining a few random ages, but the usual approach takes too long to identify instances properly. Our algorithm appears to have made the most inaccurate predictions for the basal cell carcinoma, which is code 3, followed by vascular lesions that is code 5, and melanocytic nevi, code 0, while actinic keratoses which have code 4, has made the fewest errors.

In order to further improve the accuracy of the proposed model from 80% by implementing parameter tuning.

References

1. Linares, M.A., Zakaria, A., Nizran, P.: Skin cancer. Primary Care **42**(4), 645–659 (2015)
2. Diepgen, T.L., Mahler, V.: The epidemiology of skin cancer. Br. J. Dermatol. **146**, 1–6 (2002)
3. Katalinic, A., Kunze, U., Schäfer, T.: Epidemiology of cutaneous melanoma and non-melanoma skin cancer in Schleswig-Holstein, Germany: incidence, clinical subtypes, tumour stages and localization (epidemiology of skin cancer). Br. J. Dermatol. **149**(6), 1200–1206 (2003)
4. Narayanan, D.L., Saladi, R.N., Fox, J.L.: Ultraviolet radiation and skin cancer. Int. J. Dermatol. **49**(9), 978–986 (2010)
5. Sharma, N., Sharma, K.P., Mangla, M., Rani, R.: Breast cancer classification using snapshot ensemble deep learning model and t-distributed stochastic neighbor embedding. Multimedia Tools Appl. 1–19 (2022)
6. Mangla, M., Shinde, S.K., Mehta, V., Sharma, N., Mohanty, S.N. (eds.): Handbook of Research on Machine Learning: Foundations and Applications. CRC Press (2022)
7. Patient Perspectives on the Use of Artificial Intelligence for Skin Cancer Screening – PMC (nih.gov)
8. The role of the affect heuristic and cancer anxiety in responding to negative information about medical tests – PubMed (nih.gov)
9. Kumari, A., Sharma, N.: A review on convolutional neural networks for skin lesion classification. In: 2021 2nd International Conference on Secure Cyber Computing and Communications (ICSCCC), pp. 186–191. IEEE (2021)
10. O'Keefe, W., Ide, B., Al-Khassaweneh, M., Abuomar, O., Szczurek, P.: A CNN approach for skin cancer classification. In: 2021 International Conference on Information Technology (ICIT), pp. 472–475 (2021).https://doi.org/10.1109/ICIT52682.2021.9491760
11. Sharma, N., Mangla, M., Mohanty, S.N., Satpaty, S.: A stochastic neighbor embedding approach for cancer prediction. In: 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), pp. 599–603. IEEE (2021)
12. Garg, R., Maheshwari, S., Shukla, A.: Decision support system for detection and classification of skin cancer using CNN. In: Sharma, M.K., Dhaka, V.S., Perumal, T., Dey, N., Tavares, J.M.R.S. (eds.) Innovations in Computational Intelligence and Computer Vision. AISC, vol. 1189, pp. 578–586. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-6067-5_65
13. Saba, T., Khan, M.A., Rehman, A., Marie-Sainte, S.L.: Region extraction and classification of skin cancer: a heterogeneous framework of deep CNN features fusion and reduction. J. Med. Syst. **43**(9), 1–19 (2019). https://doi.org/10.1007/s10916-019-1413-3
14. Kumar, P.R., Katti, A., Mohanty, S.N., Senapati, S.N.: A deep learning-based approach for an automated brain tumor segmentation in MR images. In: Gupta, D., Goswami, R.S., Subhasish Banerjee, M., Tanveer, R.B., Pachori (eds.) Pattern Recognition and Data Analysis

with Applications, pp. 87–97. Springer Nature Singapore, Singapore (2022). https://doi.org/10.1007/978-981-19-1520-8_7
15. Kumar, P.R., Sarkar, A., Mohanty, S.N., Kumar, P.P.: Segmentation of white blood cells using image segmentation algorithms. In: 2020 5th International Conference on Computing, Communication and Security (ICCCS), pp. 1–4. IEEE (2020)
16. Sharma, N., et al.: A smart ontology based IoT framework for remote patient monitoring. Biomed. Signal Process. Control **1**(68), 102717 (2021)
17. Sharma, N., Dev, J., Mangla, M., Wadhwa, V.M., Mohanty, S.N., Kakkar, D.: A heterogeneous ensemble forecasting model for disease prediction. N. Gener. Comput. **39**(3), 701–715 (2021)