International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

Enhancing Skin Cancer Classification on the PH2 Dataset Through Transfer Learning Technique

Dr Latha M[1], Dr Manjula G[2], Dr Raghavendra Y M[3], Keerthi Kumar M[4], Rashmi H C[5]
[1,2,3] Associate Professor, Department of Electronics and Communication Engineering, GSSS Institute of Engineering and Technology for Women, Mysuru, Karnataka, INDIA, Affiliated to VTU, Belagavi, Karnataka, India.
[4,5] Assistant Professor, Department of Electronics and Communication Engineering, GSSS Institute of Engineering and Technology for Women, Mysuru, Karnataka, INDIA, Affiliated to VTU, Belagavi, Karnataka, India.
Email id: *latha@gsss.edu.in[1]*

Abstract
Skin, the largest organ of the human body, serves as a crucial barrier against external threats. Among the myriad skin diseases, melanoma, or skin cancer, stands out as one of the most perilous and lethal conditions. However, its prognosis dramatically improves when detected early. The advent of advanced diagnostic imaging methods has mitigated the risks associated with cancer treatment, facilitating precise diagnoses and enhancing treatment efficacy. The development and evaluation of image processing algorithms for medical image analysis heavily rely on the availability of medical images. In this study, we utilize dermoscopic images sourced from the PH2 database for analysis. Our results demonstrate that the Skin Cancer Classification (SCC) system, employing Convolutional Neural Networks (CNN), outperforms traditional methods in terms of accuracy (98.5%), specificity (100%), and sensitivity (97.5%) across both stages of evaluation. From the analysis, it is evident that the superiority of CNN-based SCC systems in accurately diagnosing skin cancer. This paper underscores the significance of leveraging advanced image processing techniques for medical image analysis, paving the way for reliable skin cancer classification systems with potential clinical applicability.

Keywords: *Deep Learning, Transfer Learning, Skin Cancer classification.*

1. Introduction
Skin cancer is among the illnesses that cause the most fatalities worldwide. Skin cancer can come in two main forms: melanoma and non-melanoma. If these lesions are found early, the cure rate may increase to 90% [4]. Visual inspection is challenging because of the many different forms of skin lesions' striking similarity, which could lead to inefficient study [3]. As a result, a computerized approach is needed for classifying skin lesions. For this classification system, artificial intelligence and image processing methods were employed. The prior computer-aided techniques for dermatological image classification suffered from two major problems. The imaging procedure, in which skin images are captured using a special tool called a dermoscopy and other medical images, such as histology images, are acquired, which is the second most challenging problem. The two most important parts of a Computer Aided Diagnosis (CAD) system are feature extraction and categorization. In the earlier stages, numerous spatial and spectral features are used, and numerous machine-learning techniques are produced in the later stage for the categorization. The color, shape, and texture of skin lesions are the primary characteristics used to categorize skin cancers. The model parameters can be employed as features and dimensionality reduction can be achieved if the skin lesion is accurately modeled using cutting-edge approaches. The parameters of the suggested model as well as common properties

like color and texture are successfully investigated in this study. This study uses deep learning because it enhances the computerized system's ability to diagnose melanoma. This paper presents the application of a Deep Convolutional Neural Network (DCNN) for the classification of color images depicting various types of skin cancer. Specifically, the DCNN is tasked with categorizing these images into three distinct types: Melanoma, atypical nevus, and common nevus. By leveraging the capabilities of DCNNs, this study aims to enhance the accuracy and efficiency of skin cancer diagnosis, thereby facilitating timely and precise medical interventions for patients. The suggested approach offers two key benefits over the earlier computer-assisted skin cancer techniques. In the Primary Phase, any form of image can be used with the suggested technique for dermoscopic and photographic images. In the Secondary Phase, there is no pre-processing necessary with the suggested approach. It employs the collected color skin pictures directly. Current work depicts the various approaches used for skin cancer detection and efficient use of the transfer learning approaches in skin cancer classification.

2. Proposed Study

2.1 Literature Survey

Advancements in both treatment and detection modalities have contributed significantly to the reduction in skin cancer mortality rates over the past three decades. The vast body of research conducted in these domains has led to substantial progress. Early detection is paramount for improving cancer prognosis, and the development of Computer-Aided Diagnosis (CAD) systems has played a pivotal role in enhancing diagnostic accuracy and efficiency. These systems leverage image processing and computational intelligence techniques to aid various healthcare professionals, including physicians, cardiologists, neuroscientists, radiologists, and healthcare technologists. This paper surveys a range of methods employed in classifying skin cancer using dermoscopic images. By exploring the landscape of research in this field, it provides valuable insights into the evolving landscape of skin cancer diagnosis and highlights the potential of CAD systems in revolutionizing medical image analysis. The incidence and mortality rates of skin cancer have been on the rise globally due to the uncontrolled proliferation of skin cells. In the USA alone, in 2018, there were approximately 91,270 new cases of melanoma with an estimated 9,320 deaths (American Cancer Society, 2018). Worldwide, in 2012, there were over 32,000 new cases of melanoma and about 55,000 associated deaths (Stewart, 2014). Notably, mortality rates tend to be higher in men compared to women. Early detection and treatment are crucial for mitigating mortality, given melanoma's propensity for rapid spread throughout the body [2]. In recent years, considerable efforts have been directed towards developing Computer-Aided Diagnosis (CAD) systems for the screening and detection of skin cancers. Abuzaghleh et al. (2015) proposed a non-invasive approach for skin lesion classification that incorporates real-time alerts for detecting skin burns. Their system utilizes texture, color, and shape features for early lesion classification, employing a Support Vector Machine (SVM) classifier. Alencar et al. (2016) introduced a Multi-Layer Perceptron (MLP) network trained on color and edge characteristics of lesions, employing the back-propagation algorithm for effective lesion classification [1]. Garnavi et al. (2012) explored melanoma diagnosis using wavelet-based features, integrating them with geometrical and border-based features. They employed various classifiers such as SVM, Random Forest (RF), Naive Bayes (NB), and logistic tree models for classification. Sadri et al. (2017) proposed a fixed grid wavelet network for melanoma diagnosis, employing the relief algorithm to select ten effective features from a multitude of color, shape, and texture features for classification purposes [5]. Yu et al. (2016) introduced a method for skin lesion segmentation and classification utilizing Convolutional Neural Networks (CNNs). Their approach employs a fully convolutional residual network for segmentation, and for classification, a deep residual network is utilized. They address the degradation problem through the use of residual

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

learning, which enhances model performance. Celebi and Zornberg (2014) proposed a skin lesion classification technique based on symbolic regression algorithms. This method leverages clinically significant colors to compute malignancy scores, aiding in the classification process. Furthermore, a K-means clustering approach is employed to reduce the number of colors in dermoscopic images, thereby facilitating subsequent analysis and classification tasks [17] [16]. Hekler et al. (2019) developed a CNN-based gradient boosting method tailored for dermatologists and artificial intelligence (AI) systems. Their approach focuses on biopsy-verified skin lesion classification and detection, distinguishing between benign and malignant tumors through 37 binary classifications. In a related study, Goyal et al. (2020) utilized AI-based image classification to diagnose various skin lesion datasets. They leveraged dermoscopy images sourced from clinical and histopathology data, showcasing the potential of AI in accurate skin lesion diagnosis. Additionally, Amin et al. (2020) contributed to distinguishing between malignant and benign lesions using various image modalities. Their research highlights the importance of integrating different imaging techniques to enhance diagnostic accuracy in lesion classification [7] [8]. Maron et al. (2019) conducted a comprehensive multiclass skin cancer classification study utilizing a CNN model, coupled with K-nearest neighbors (KNN) algorithm and Support Vector Machine (SVM) classifier for deep learning techniques. Their research focused on biopsy-verified images, emphasizing the primary endpoint of distinguishing between benign and malignant diseases. In a related effort, Mahbod et al. (2020) proposed a multi-network ensemble approach for skin lesion classification. Their study introduced a secondary endpoint, aiming for the accurate classification of images into different categories, showcasing the efficacy of ensemble methods in enhancing classification accuracy. Furthermore, to address challenges related to image quality and resolution, a multi-CNN multi-scale blending mode technique was employed for image enhancement. This technique enables effective subsampling or cropping of skin lesion images, thereby enhancing the robustness and performance of the classification models [10] [14]. Ghalejoogh et al. (2020) introduced a hierarchical structure-based stacking ensemble method for dermoscopy image evaluation, utilizing datasets from PH2 and Gangster with five-fold cross-validation. Their approach aimed to improve classification performance through the integration of heterogeneous classifiers with meta-learning techniques. Qin et al. (2020) proposed a skin lesion classification system employing generative adversarial networks (GANs)-based image synthesis along with heterogeneous classifiers and meta-learning methods. Their approach emphasized accurate diagnosis through improved performance [6]. Rodrigues et al. (2020) developed a skin cancer classification system applicable to IoT platforms, enabling doctors to access diagnosis assistance anytime and anywhere. Their system, aided by an Artificial Neural Network (ANN) model, ensures objective diagnoses with minimal subjective factors. Harangi et al. (2020) introduced a system integrating the visual geometry group system and deep learning framework for skin cancer classification. Utilizing various neural network algorithms and the ResNet system, their approach provides real-time network models for cancer classification. The Table 1 provided summarizes the datasets used in recent studies on skin cancer classification, reflecting the diverse contributions of researchers towards improving prevention and detection in this domain [12] [13].

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

Table 1 Summarizes the Skin Cancer Datasets

Dataset category	Datasets	Source/ reference	Category	Instances	Features/ attributes	No. of classes	Missing values
Skin lesion	PH2 (Mendonça et al., 2013)	ADDI (2020)	Multiclass	200	15	03	NO
	HAM10000 (Tschandl et al., 2018)	ViDIR (Dataverse, 2020)		10,015	192	07	NO
	MED-NODE (Giotis et al., 2015)	MED-NODE (Rug, 2020)	Binary class	140	112	02	NO
	Dermatology Atlas (Kim et al., 2004)	Derm. Atlas (Dermoscopy Atlas, 2020)	Multiclass	250	112	03	NO
	Dermnet - Atlas (Liao et al., 2016)	Dermnet.Atlas (Dermnet, 2020)	Binary class	180	112	02	NO
	Dermis (Xu et al., 2018)	Dermis (2020)	Binary class	210	112	02	NO
Others (non-skin lesion)	Heart-C	KEEL (2020)	Multiclass	303	13	05	YES
	Heart-Statlog	KEEL (2020)	Binary class	270	13	02	NO
	Hepatitis	KEEL (2020)	Binary class	155	19	02	NO
	Iris	KEEL (2020)	Multiclass	150	04	03	NO
	Letter	KEEL (2020)	Multiclass	20,000	16	26	NO
	Mushroom	KEEL (2020)	Binary class	8,124	22	02	YES
	Diabetes	UCI (2020)	Multiclass	20,201	04	20	NO
	Segment	UCI (2020)	Multiclass	2,310	19	07	NO
	Sick	UCI (2020)	Binary class	2,800	29	02	YES
	Soybean	UCI (2020)	Multiclass	307	35	19	YES

2.1 Methodology

Diagnosing skin cancers, particularly melanoma, presents a significant challenge even for experts due to the absence of a simple set of noninvasively obtainable indicators for near-perfect diagnosis. Efforts in public awareness campaigns and educational initiatives for general practitioners (GPs) have provided valuable insights and diagnostic aids. Timely intervention, particularly through early removal of lesions before invasion and metastasis, significantly improves the prognosis for skin cancer patients. Consequently, there's a pressing need to enhance the speed and accuracy of primary care diagnosis, emphasizing the importance of earlier detection and prompt referral. However, the complexity and skill required for accurate diagnosis, combined with the vast breadth of knowledge demanded of GPs, often exceeds what can be reasonably expected in primary care settings. This underscores the necessity for diagnostic support tools. This paper aims to propose a system architecture for skin cancer diagnosis leveraging image processing and machine learning techniques, primarily utilizing dermoscopic images. Figure 1 illustrates the proposed system's components and workflow, aiming to assist healthcare professionals in making more accurate and timely diagnoses. The Large variety of categorized images makes it difficult to build a deep neural network. Switch learning and photo zooming are applied to the pre-trained AlexNet to accomplish this important task. The proposed method has the potential to score three distinct errors by replacing the last SoftMax level with only 3 lessons. According to the transfer study, the weights of the revised version have been qualitatively refined, similar to the expansion of the dataset. The proposed technique as shown in the Figure 1 has most important benefits over the sooner pc-aided techniques for skin most cancers. First, the proposed method has the capacity to paintings with any kind of picture (dermoscopic and photographic). 2nd, the proposed technique does not require any pre-processing. It works immediately with the received color pix of pores and skin.

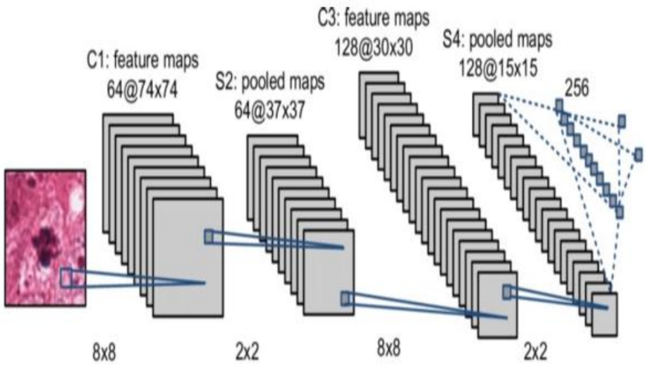

Figure 1 Proposed Architecture

a. Images

Skin Cancer is one of the most common types of disease in the United States [9]. In this paper, the image of skin cancer that normally present in the form of RGB. These images represent having the cancer on the human body as shown in the Figure 2, 3and 4.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

Figure 2 Skin Cancer Images of Vascular Lesions

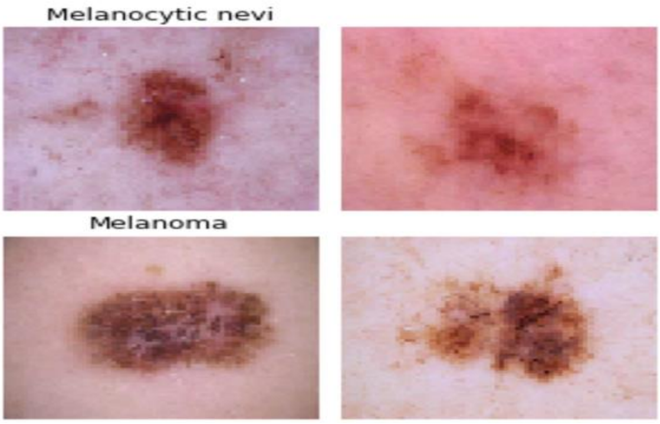

Figure 3 Skin Cancer Images of Melanocytic and Melanoma

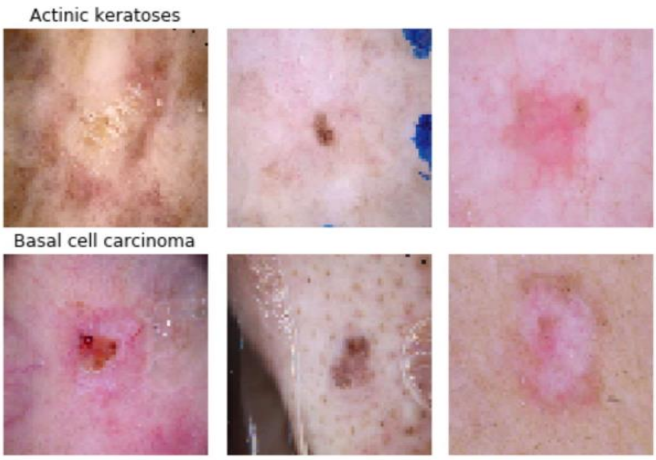

Figure 4 Skin Cancer Images of Actinic and Basal

b. Preprocessing

In this process, the image used in the analysis was converted into gray format. In this transformation, it is able to adjust the edges of the image and automatically that image converted into RGB to gray scale. Then further adding the erosion and dilation to that image.

c. Transformation

Training a new CNN model requires a large number of images. Unfortunately, no skin lesion dataset is available with thousands of annotated images. Transfer learning theory is a key solution to this difficult problem, where a large set of medical data like ImageNet can be leveraged within AlexNet. In the proposed model, three different methods were applied to AlexNet: First, the last level used for classification was replaced with a new softmax level to classify input images into three classes instead of 1000 as in ImageNet. Second, backpropagation was used to refine the weights to generate new weights to better classify the skin lesions. A slow learning rate is used so that the convolutional layer weights do not change drastically while the fully connected layer weights are randomly initialized. [11] [15]

d. Classification

CNNs show high performance as advanced skin lesion classifiers. Unfortunately, it is difficult to compare different classification methods because some approaches use non-public datasets for training and/or testing, making reproducibility difficult. Future publications should use publicly available references and fully disclose training methods to allow for comparability. CNNs can be included in the classification by removing fully connected CNN layers that have been pre-trained on a large data set. When classifying skin lesions, initial training is done with ImageNet. Despite the non-medical domain of the image, the learned features are of sufficient quality to classify lesions. Finally, semantic sentiment analysis concept is used which is mainly concerned about the semantic meaning of the word. It could be divided into two types: contextual semantics and conceptual semantics. Conceptual semantic information about

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

a function that can be integrated with the Naïve Bayes machine learning method to improve sentiment analysis performance.

2.2 Experimental Results

The significance of automated pattern recognition systems for skin cancer diagnosis is underscored by the substantial research interest, particularly in dermoscopic image classification. Many crucial diagnostic indicators used in clinical assessment, such as size, border irregularity, notching, and asymmetry, can be extracted from various sources of information. The extent of the lesion is a critical factor for analyzing features such as color and texture within the lesion area. These features are essential for identifying malignancy in melanoma accurately. The features incorporated into the system can be categorized into three main groups:

Color Moments: Statistical properties of local color information.

Modeling Parameters: Parameters representing spatial and frequency domains.

Spatial Patterns: Spatial characteristics of skin lesions captured during analysis. By leveraging these diverse sets of features, the automated system can effectively capture and analyze the complex patterns present in dermoscopic images, enhancing the accuracy of skin cancer diagnosis.

Figure 5 Results Computed for Skin Cancer Classification using CNN Model

The classification scenario described follows a two-stage deep learning approach. In the first stage, the system classifies images as either normal or abnormal, while in the second stage, it further classifies abnormal cases into benign or malignant. The significance of color in skin lesion diagnosis is widely acknowledged, with color providing crucial information for identifying lesion boundaries. Features such as specific shades and color variability play a vital role in diagnosis, often included in skin cancer checklists and descriptions for differential diagnosis. Results computed for skin cancer classification using CNN model are shown in Figure 5.

Table 2 Comparative Study of Dermoscopic Databases

Database	#Images used	A_c	S_n	S_p
PH^2	200	-	97.5	96
Caucasian race dataset includes PH^2	360	91.1	83.3	95
PH^2	200	97.5	97.7	96.7
PH^2	200	87.33	87.08	88.13
PH^2	200	90.50	90	91.25
PH^2	200	95.3	95	96.25

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

Table 3 Comparative Study of Classification Methods

Classification Method	TPR (%)	TNR (%)	PPV (%)	ACC (%)
Symmetry type	67	89	69	83
Joint Reverse	87.50	93.13	----	92
ANN	90.86	96.11	92.38	92.5
SVM	97	84	----	96
DCNN	**98.33**	**98.93**	**97.73**	**98.61**

Table 4 Performance Measure of Proposed Model

Average accuracy (%)	Average sensitivity (%)	Average specificity (%)	Average Precision (%)
80	72.92	83.33	75.81
98.61	**98.33**	**98.93**	**97.73**

Tables 2, 3, and 4 summarize comparisons across dermoscopic databases, classification methods, and performance measures of the proposed model. Given the two-stage classification process, performance measures such as accuracy (Ac), sensitivity (Sn), and specificity (Sp) represent average performances across both stages. The analysis utilizes the same set of training and testing images for consistency. Results indicate that the CNN model outperforms existing approaches, yielding promising results compared to recent studies by Hekler et al. (2019), Maron et al. (2019), and Rodrigues et al. (2020). However, achieving higher performance with CNN necessitates a larger number of training images. Overall, these findings underscore the potential of the proposed CNN-based model in enhancing skin cancer diagnosis, offering improved accuracy and reliability compared to previous methodologies.

Conclusion

In this study, a model is trained on neural networks to classify seven different forms of skin cancer using transfer learning. Early detection of skin cancer is critical for successful treatment, yet it remains challenging to diagnose at later stages. We explore utilizing the output of base layers as inputs to classical machine learning algorithms like Support Vector Machines (SVM) and other ensemble models. This approach enables a deeper understanding of the model by incorporating machine learning models as the top layers, potentially enhancing classification accuracy. Understanding how Convolutional Neural Networks (CNNs) process images is crucial, especially in medical applications where interpretability is essential. CNNs are often perceived as "black boxes," and interpreting them can provide valuable insights for future research, particularly in the medical domain. Furthermore, incorporating image segmentation techniques to isolate skin lesions may reduce noise in input data, potentially improving classification performance. However, our study suggests that the proposed method outperforms this approach. To further advance this research, future studies could explore larger model architectures and conduct more extensive fine-tuning with increased computational and memory resources. Expanding the scope of analysis may lead to further improvements in skin cancer classification accuracy and pave the way for more effective diagnostic tools

References

[1]. Abuzaghleh, O., Barkana, B. D., & Faezipour, M. (2015). Noninvasive real-time automated skin lesion analysis system for melanoma early detection and prevention. IEEE journal of translational engineering in health and medicine, 3, 1-12.

[2]. Bw, S., & Wild, C. P. (2014). World cancer report 2014. Lyon, France: World Health Organisation, 16-27.

[3]. Codella, N., Cai, J., Abedini, M., Garnavi, R., Halpern, A., & Smith, J. R. (2015, October). Deep learning, sparse coding, and SVM for melanoma recognition in dermoscopy images. In Machine Learning in Medical Imaging: 6th International Workshop, MLMI 2015,

e ISSN: 2584-2137
Vol. 02 Issue: 03 March 2024
Page No: 500 - 507
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0072

Held in Conjunction with MICCAI 2015, Munich, Germany, October 5, 2015, Proceedings (pp. 118-126). Cham: Springer International Publishing.

[4]. Codella, N. C., Nguyen, Q. B., Pankanti, S., Gutman, D. A., Helba, B., Halpern, A. C., & Smith, J. R. (2017). Deep learning ensembles for melanoma recognition in dermoscopy images. IBM Journal of Research and Development, 61(4/5), 5-1.

[5]. Garnavi, R., Aldeen, M., & Bailey, J. (2012). Computer-aided diagnosis of melanoma using border-and wavelet-based texture analysis. IEEE transactions on information technology in biomedicine, 16(6), 1239-1252.

[6]. Ghalejoogh, G. S., Kordy, H. M., & Ebrahimi, F. (2020). A hierarchical structure based on stacking approach for skin lesion classification. Expert Systems with Applications, 145, 113127.

[7]. Hekler, A., Utikal, J. S., Enk, A. H., Hauschild, A., Weichenthal, M., Maron, R. C., & Thiem, A. (2019). Superior skin cancer classification by the combination of human and artificial intelligence. European Journal of Cancer, 120, 114-121.

[8]. Kiran Babu, N. S., & Madhusudhana Reddy, D. E. (2021, April). Development of Novel Classifying System to Predict the Calcaneal Shift Using Deep Convolution Neural Networks. In Proceedings of the International Conference on Innovative Computing & Communication (ICICC).

[9]. Mishra, N. K., & Celebi, M. E. (2016). An overview of melanoma detection in dermoscopy images using image processing and machine learning. arXiv preprint arXiv:1601.07843.

[10]. Maron, R. C., Weichenthal, M., Utikal, J. S., Hekler, A., Berking, C., Hauschild, A., & Thiem, A. (2019). Systematic outperformance of 112 dermatologists in multiclass skin cancer image classification by convolutional neural networks. European Journal of Cancer, 119, 57-65.

[11]. Nirupama, P., & Reddy, E. M. (2019). Development of Novel Classifying System to Identify the Right Sense of Image Sharing in Social Networks Using Deep Convolution Neural Network. Indian Journal of Public Health Research & Development, 10(7), 1244-1247.

[12]. Rodrigues, D. D. A., Ivo, R. F., Satapathy, S. C., Wang, S., Hemanth, J., & Reboucas Filho, P. P. (2020). A new approach for classification skin lesion based on transfer learning, deep learning, and IoT system. Pattern Recognition Letters, 136, 8-15.

[13]. Rajendran, G. B., Kumarasamy, U. M., Zarro, C., Divakarachari, P. B., & Ullo, S. L. (2020). Land-use and land-cover classification using a human group-based particle swarm optimization algorithm with an LSTM Classifier on hybrid pre-processing remote-sensing images. Remote Sensing, 12(24), 4135.

[14]. Subramani, P., & BD, P. (2021). Prediction of muscular paralysis disease based on hybrid feature extraction with machine learning technique for COVID-19 and post-COVID-19 patients. Personal and ubiquitous computing, 1-14.

[15]. Tarver, T. (2012). American cancer society. Cancer facts and figures 2014. J Consumer Health Internet, 16, 366-367.

[16]. Totakura, V., Reddy, E. M., & Vuribindi, B. R. (2021). Symptomatically Brain Tumor Detection Using Convolutional Neural Networks. In IOP Conference Series: Materials Science and Engineering (Vol. 1022, No. 1, p. 012078). IOP Publishing.

[17]. Yu, L., Chen, H., Dou, Q., Qin, J., & Heng, P. A. (2016). Automated melanoma recognition in dermoscopy images via very deep residual networks. IEEE transactions on medical imaging, 36(4), 994-1004.