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A Comprehensive Guide To Melanoma Cancer Prediction

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***Abstract*— Melanoma, a highly serious form of skin cancer, poses a significant threat if not detected early, potentially leading to mortality. Traditional diagnostic methods involve dermatologists utilizing microscopes to analyze and convey biopsy results, a challenging and skill-dependent process. Recognizing the need for a more efficient and accurate diagnosis, artificial intelligence (AI) methods offer a promising solution. In our research, we explored the application of neural network learning and dermatological image processing for melanoma identification. Our investigation encompassed various convolutional neural network (CNN) Design, including VGG19, MobileNetV2, ResNet50V2, DenseNet201, Exception, VGG17, GoogleNet, and ResNet152V2. These models were evaluated based on their performance using deep learning on graphics processors. Processing a dataset of 7056 photos, we compared the outcomes of these models. Notably, GoogleNet exhibited the most accuracy in both training and test sets, achieving 73.93% and 77.09%, respectively. This highlights the potential of AI-driven approaches, particularly GoogleNet, in enhancing the efficiency and precision of melanoma diagnosis in comparison to traditional methods.**

Keywords—Melanoma skin cancer, CNN (Convolutional Neural Network), Deep learning, Artificial Intelligence, Image processing

I. INTRODUCTION

Melanoma cancer is prevalent kinds of cancer, beginning with the unstable proliferation of skin dead cells. UV radiation form the sun or tanning booths may lead cells in the skin to proliferate and create malignant tumors. Skin disease is common in many causes of mortality globally. In 2023, 98,160 Americans received diagnoses by skin cancer, which represents 5% of total cases of cancer in the US. Additionally, 7980 individuals died as a result of skin cancer, accounting for 1.31% of total fatalities in the country [1]. Melanoma is important prevalent and severe kinds of skin cancer, spreading fast to other regions of the physique. Skin melanoma has a 4-year survival rate of 93.45%, which is rather high [1]. Early recognition of cutaneous melanoma leads to a five-year survival rate of 99 percent [1]. Skin melanoma has a higher probability of recovery when it is confined and haven't spread to other part of the body. Anyhow, only 75.69% of skin melanomas are discovered at this stage. Early detection of cutaneous melanoma can lower mortality rates. Dermatologists often use ocular exams to diagnose skin cancer, with an accuracy rate of around 60.12% [2]. Dermoscopy improves diagnosis accuracy for skin malignancies by 90%. Dermoscopy is very sensitive in identifying skin malignancies, with a sensation of 87.45% is melanocytic lesions, 86.78% for squamous cell carcinoma and 96.78% for basal cell carcinoma, [3]. Although dermoscopy improves the melanoma detection accuracy, it can remain to be difficult for diagnosing effectively certain tumors, especially early melanomas that lack distinguishing markers. Although dermoscopy accurately identifies cutaneous melanoma, it is not suitable for identifying featureless melanoma. Further accuracy improvements are needed to boost patient survival rates. The challenges of dermoscopy and the desire for more accurate skin cancer diagnosis led to the development of computer-aided detection technologies.

The process of computer-aided skin disease detection commonly consists of five key stages: image capture, pre-processing, segmentation, feature extraction, and classification [4,5]. Segmentation and classification play pivotal roles in computer-aided skin cancer detection [6, 7]. Achieving accurate diagnoses in skin cancer through computer-aided methods demands meticulous attention to various criteria. Deep-learning based approaches outperformed other computer-assisted methods in dividing and categorizing lesions of the skin by extracting intricate data from photos in greater detail. The deep-learning techniques are very efficient and capable of learning

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specific to the job properties. This article highlights recent research on using algorithmic deep learning to properly identify skin cancer. This review paper can help create predictive and efficient AI methods for melanoma cancer diagnosis.

Convolutional neural networks (CNN), a sort of deep learning technology, have shown success in extracting features from pictures to identify associations [10-13]. In our research domain, the application of deep convolutional neural networks has proven instrumental for interpreting medical images, specifically in tasks related to the identification of melanoma. More research and tests may be required to achieve very accurate findings. Convolutional neural networks can enhance patient care by providing accurate diagnoses for cancers, particularly melanoma skin cancer. This study focuses on a strategy that can produce positive outcomes. Several publications [13,14] refer to convolutional neural networks as black-box models.

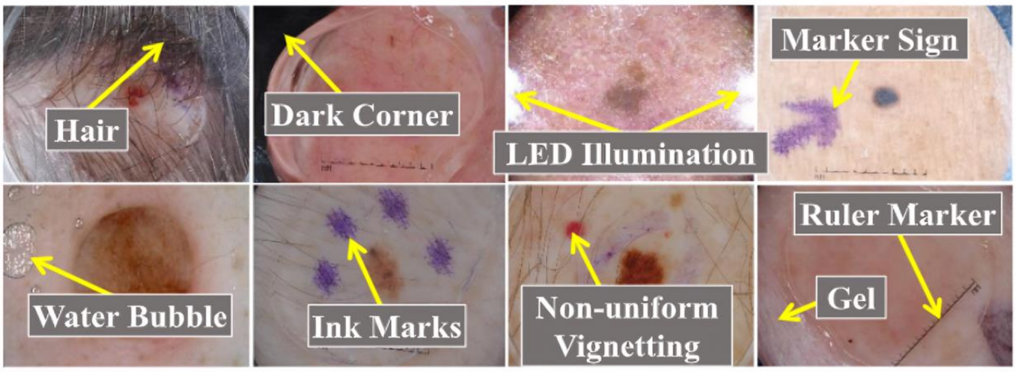

Figure 1 shows skin tumors with artefacts modified from [8].

In Table 1, various reviews on skin cancer detection are outlined, authored by Adegun and Viriri [10], Lucieri et al. [11], Dildar et al. [12], Pacheco and Krohling [13], and Gilani and Marques [14]. Notably, this study distinguishes itself by specifically reviewing the latest research released in 2021 and 2022, a departure from the content covered in earlier reviews within the field.

Table 1: Review Summary

Paper	**Year**	**Scope**
Pacheco and Krohling [13]	2019	Studied neural network algorithms for skin cancer categorization.
Lucieri et al. [11]	2021	Recommended deep-learning-based guidance for skin tumor detection.
Adegun and Viriri [10]	2021	Studied advanced machine learning methods for cancer of the skin classification.
Dildar et al. [12]	2021	Reviewed neural network methods for cancer of the skin classification.
Gilani and Marques [14]	2023	Applied GANs, or generative adversarial networks, are used to classify and separate skin lesions.

To diagnose skin cancer accurately, quickly, and with flexibility, it's important to examine alternatives to conventional biopsies. This study intends to enhance the diagnosing process compared to existing methods. Deep learning is a new data science subject that extends machine learning. Research has demonstrated that deep learning approaches are more flexible than machine learning methods [15-17].Big data has facilitated development and success in this sector [18, 19]. Machine learning algorithms have been influenced by the natural brain, specifically the vast number of deeper neurons found in the retina [16,20-22]. A convolutional neural systems have gained popularity in several sectors for their superior image processing capabilities. In medicine, they have been used to diagnose and treat conditions. Advancements in technology led to the usage of techniques based on deep learning for superior tasks, particularly in the medical field for identifying and treating illnesses. Accurate detection of malignancies, especially melanoma, is challenging [23].figure 2 shows the various skin cancer.

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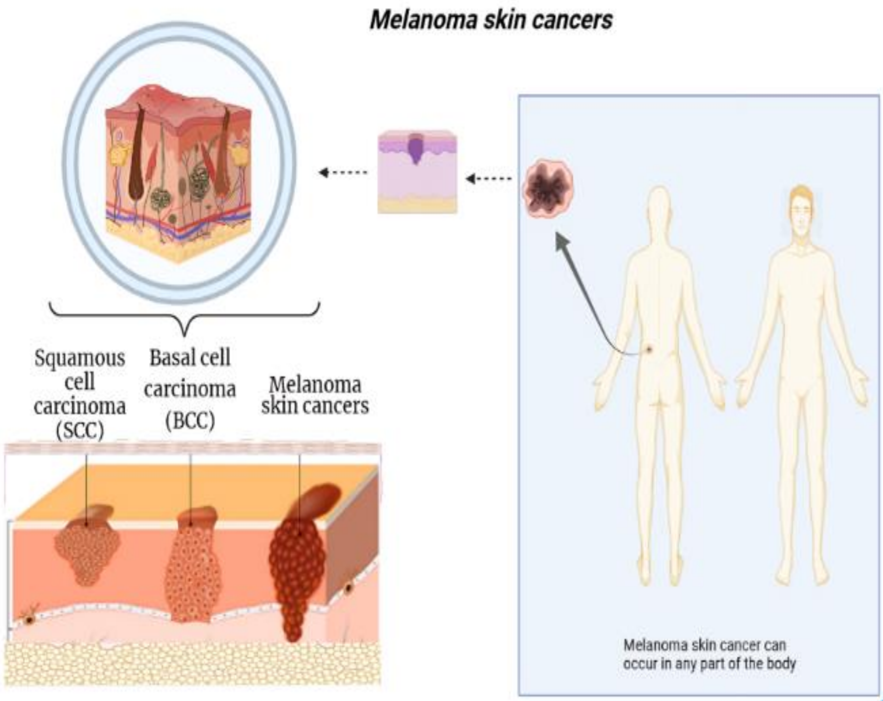

Figure 2. An overview of melanoma skin cancers.

II. METHODOLOGY

A. Dataset

The study we conducted employed the 2019 edition of the International Melanoma Imaging Collaboration (IMIC) Dataset [16-19]. Dataset was retrieved from https://challenge.imic-archive.com/ on October 6, 2021. The database comprises 24,283 photos, 7264 of which are pertinent to the present topic of survey, including 4502 photographs of cancer related to skin.

B. Preprocessing

Image processing involves enhancing or extracting details from a picture using different techniques. picture editing involves taking a picture as input and producing either an additional picture or related attributes or qualities. Image augmentation improves an image's visual appeal, which renders it easier to interpret or analyze. Technologies like as colour expanding, histogram equalization, and brightening can help achieve this. nclusion of images in the dataset was determined through an analysis of their metadata marks. This dataset is divided into two primary classes: images captured by thermoscopic analysis categorized as either dangerous or favorable. The proposed system is structured across three levels. Training datasets are placed in the input layer, often known as the first layer. The input layer weighs provided data before it moves on to the hidden levels. Neurons in buried layers separate data characteristics to discover patterns. The pattern serves as the foundation for the output layers, which choose the appropriate classes. Finally, binary classification successfully selects classes 1–6. The case involves melanocytic nevi, pyogenic granulomas, fibrosis of, active keratoses, intraepithelial carcinoma, benign keratosis-like lesions, is a cancer of basal cells, and hemorrhage. Melanoma is the ultimate category.

C. Segmentation & Feature Extraction:

Segmentation divides a picture into sections based on comparable pixel values or attributes. This may be accomplished by techniques like as thresholding, edge identification, and region growth. For classifying and identifying diseases by extracting characteristics from images done by feature extraction. We use Keras' Pagerank module to identify the sickness associated with a skin lesion. Most computational imaging and cv applications, such as object identification, image collection, and analysis of scene, rely on extraction of features. The feature extraction approach employed is determined on the specific task at hand as well as the features of the pictures being examined.

D. Deep Neural Network Approach

We used seven prominent DL models to compare their efficiency disparities. the VGG15 model comprises the fourteen convolutional layers, 5 maximum extracting layers VGG17 comprises of 17 convolutional layers, 5 layers with maximum extracting and extraction of features, and 4 fully synced layers for classification [20]. GoogleNet uses nine origination sections for feature extraction and fully coupled layers during classification [20]. Exception replaces the inception module incorporates deeper separable convolutions, succeeded by fully synced layers for classification [11]. DenseNet201 commences with an initial convolutional layer and a subsequent max-pooling layer, followed by four dense blocks with [6, 12, 18] layers in each block. Transitional layers among heavy blocks, and an identification layer (42). Versus ResNet50, the which consists of 50 layers of convolutional neural networks, 1 the maximum extraction, 1 normal extraction, and 1 fully synced layer for classification.[13], The latest version of Res is a updated version that employs a new residual unit [14]. Similarly, ResNet151V2 is an updated version of The ResNet architecture152 with 142 convolutional layers. 1 max-extracting, 1 average extracting, and 1 synced linked layer for classification [13, 14].MobileNetV2 differs from MobileNet in that it uses a new layer module, resulting in efficient models for mobile apps [9]. We utilized pre-trained algorithms to extract characteristics from photos and adjusted them. Figure 3 illustrates a computer deep learning strategy for discriminating among glioblastoma and non-melanoma skin cancer photos [9]. We developed an efficient network for identifying melanoma skin cancer using deep learning architectures such as TensorFlow, Colaboratory, and convolutional neural networks.

Our goal was to construct a convolutional neural network model to identify melanoma skin cancer. This program identifies common traits in photos and assigns them to appropriate categories. This technique improves classification efficiency by extracting and converting picture characteristics into a new image. Additionally, it effectively decreases image size for accurate depiction. Our the individual's categorization is a binary, with (1) indicating melanoma skin cancer and (0) denoting non-melanoma. Data was extracted via an information file and transformed to a 224 by 224 picture size for the extraction of features. We tested and examined how neural network convolution topologies affect the outcome of melanoma skin cancer. This study included eight designs, including DenseNet201, GoogleNet, exception, MobileNetV2, VGG16, ResNet152V2, VGG19, and ResNet50V2. The data were separated into three sets: training, verification, and test. Figure 3 illustrates how the model that had been trained was verified using the third set. The project was implemented using Google Colaboratory. Python libraries used include TensorFlow, Keras, pandas, NumPy, matplotlib, sklearn, scipy, torch, and seaborn.

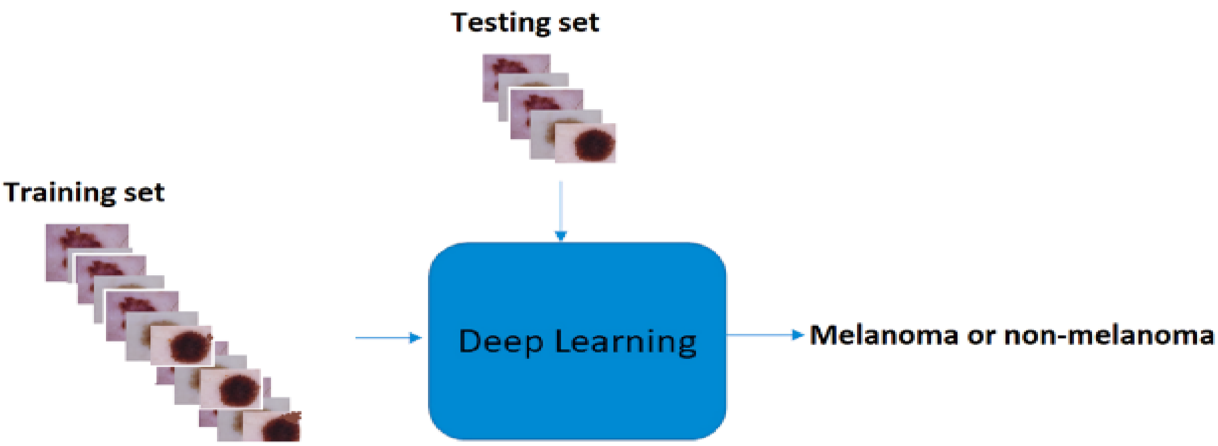

Fig 3: The deep learning framework

The procedure may be condensed into six steps. The first process included extracting data from the collection of data independently. Images were processed before being divided into data sets. Then, the actual development stage carried out for several. The design elements and accompanying findings were evaluated in the following two steps. The testing step involved running tests on the testing set sample. Measurements were taken to evaluate the architectures used to construct models and the implementation phase after storing them. The best achieved values were then compared.

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III. RESULT

You may see a graph that shows confirmation and training accuracy. As the number of epochs rises, accuracy improves in both training and validation. The precise period value used determines both training and verification accuracy, as seen in figures 4 and 5 below.

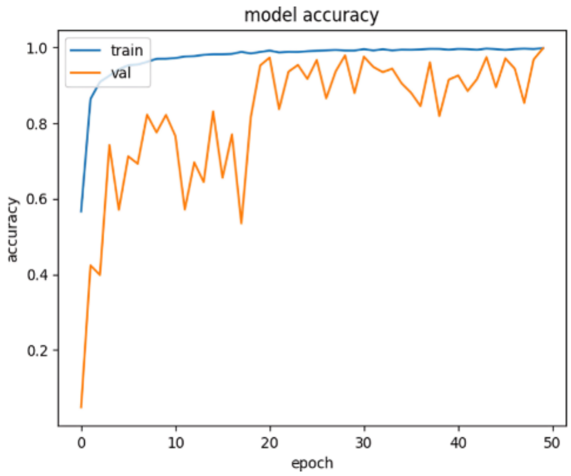

Fig 4 Graph depicting validation and training accuracy trends.

When the value of a period grows, the loss graphs for the validation and training phases diminishes until it is almost unnoticeable.

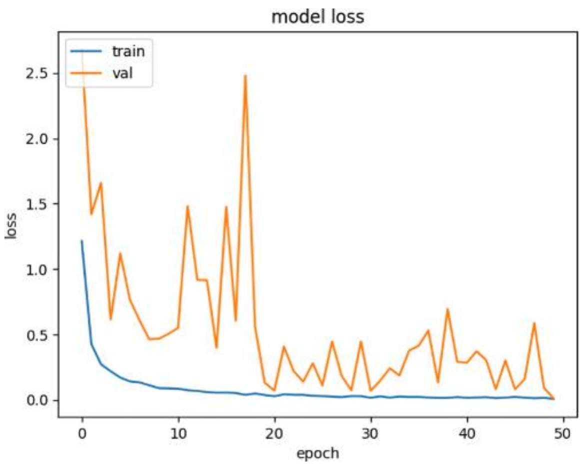

Fig 5: Graph depicting training and validation loss trends.

Achieved accuracy test: 97.11%.
x_model=np.array(x_model).reshape(- 1,27,27,4)
lost ,accuracy = testmodel.evaluate(x_model, y_model, verbose=2).
The preceding words highlight the overall test outcome achieved as it outcome.
61/61 - 1s, lost :0.1820, accuracy: 0.9501

Model trained accuracy achieved: 98.8%. Validated accuracy achieved: 99.51 percent.
The ultimate validated accuracy reached is depend on the 40th time period value (time period 40/40 = 237/237). -3s 8ms/step – loss value: 0.0056 - accuracy: 0.9777 – loss value: 0.0319 -accuracy value: 0.9691

IV. CONCLUSION

Ultimately, there is a chance to significantly increase the precision and efficacy of skin cancer diagnosis through the use of machine learning algorithms for skin cancer detection and classification. Machine learning models can reliably discriminate between benign and malignant skin lesions by assessing several characteristics of the lesions, providing doctors with valuable assistance throughout the diagnostic process. Further study is needed to address difficulties such as data scarcity and models accessibility, as well as to develop more trustworthy and accurate models. Nonetheless, the advances made in this field represent a promising step toward faster and more effective skin cancer identification and therapy. Our findings revealed that the model we developed achieves a diagnostic accuracy of around 95.13% when compared to the existing system, and the results suggest that the set models can help dermatologists properly diagnose skin lesions while reducing the danger of misdiagnosis.

More complex feature extraction algorithms that can distinguish minute differences between lesions of the skin and non-lesions might increase the predicting technique's accuracy. Using advanced methods for image processing like texture analysis, color investigation, or deep learning approaches, for instance, can improve the model's ability to distinguish between skin lesions and non-lesions.

REFERENCES

[1]. Dalhal, L. and Martí, R. [2] Hasan, M.K.; Samarakoon, P.N.; Tushar, F.I.; DSNet: Segmentation of dermoscopic skin lesions automatically. Biomed. Comput. 2020, 120, 103738
[2]. Ahmed, S.; Dengel, A.; Lucieri, A. Deep Learning-Based Medical Decision Support: An Analysis of Skin Cancer Diagnosis Case Study arXiv:2103.051112, arXiv:2021.
[3]. Past developments in deep learning applied to skin cancer diagnosis by Pacheco, A.G. and Krohling, R.A. arXiv 2019, arXiv:1912.03280.
[4]. Viriri, S. Adegun, A. Deep learning methods for melanoma cancer diagnosis and skin lesion analysis: An overview of cutting-edge approaches. Artif. Intell. Rev. 2021, 54, 811–841.

[5]. Marques, Gilani, S.Q. ; O. Generative adversarial networks for skin lesion analysis: A review. Appl. Multimed. Tools 2023, 1–42.
[6]. Mahnashi, M.H. Deep learning algorithms for skin cancer detection: A review 2021; Int. J. Environ. Res. Public Health 18, 5479.
[7]. Inthiyaz, S.; Ahammad, S.H.; Altahan, B.R.; Rajesh, V.;Smirani, L.K.; Hossain, M.A.;Kalangi, R.R.; Rashed, A.N.Z. Skin disease identification using deep learning. Adv. Eng. Softw. 2023, 175, 103361.
[8]. D.R. Nayak, M.A. Zaveri and H.K. Gajera, a thorough examination of dermoscopy pictures using deep CNN characteristics to identify melanoma Biomed. Signal Process. Control 2023, 79, 104186.
[9]. Marchetti, M.; Mishra, N.; Halpern, A.; Gutman, D.; Codella, N.C.; Celebi, E.; Helba, B. An obstacle in melanoma identification by skin lesion analysis was presented at the 2016 International Symposium on Biomedical Imaging (ISBI), which was organized by the International Skin Imaging Collaboration (ISIC). arXiv:1605.01397; arXiv:2016.016377.
[10]. Chollet, F. Xception: Deep learning using depthwise separable convolutions. In Honolulu, Hawaii, USA, July 21–26, 2017, IEEE Conference on Computer Vision and Pattern Recognition Proceedings, pp. 1251–1258.
[11]. Gouda, W.; Sama, N.U.; Al-Waakid, G.; Humayun and M.; Jhanjhi, N.Z.Deep learning-based skin lesion image detection for skin cancer Healthcare 2022, 10, 1183.
[12]. Iandola, F.N.; Ashraf, K.; Dally, W.J.; Keutzer, K.; Han, S.; Moskewicz, M.W. SqueezeNet: <0.5 MB model size and 50x fewer parameters with accuracy comparable to AlexNet.arXiv2016,arXiv:1602.07360.
[13]. "Skin Cancer Classification Using Image Processing and Machine Learning," Arslan Javaid, Muhammad Sadiq, and Faraz Akram, IEEE, 2021
[14]. Samia Islam, Ahmed Wasif Reza "Convolutional Neural Network (CNN) for Skin Cancer Detection," Research Gate, conference paper 2019
[15]. In the proceedings of the International Conference on Electronics and Sustainable Communication System (ICESC 2020), S. Subha, Dr. D. C. Joy Winnie Wise, S. Srinivasan, M. Preetham, and B. Soundarlingam distinguishing between rashes and skin cancer
[16]. International Journal of Recent Technology, Mahmudul Hasan, Mohammad Mohsin, and Md. Kamal Hossain Chowdhury, "Automatic Detection and Analysis of Melanoma Skin Cancer using Dermoscopy Images"
[17]. Bhuiyan, M.Z.A.; Wang, G.; Gheisari, M. a survey on big data and deep learning. Volume 2, pages 173–180, Proceedings of the 2017 IEEE International Conference on Embedded and Ubiquitous Computing (EUC) and Computational Science and Engineering (CSE), Guangzhou, China, July 21–24, 2017.
[18]. Liang, G.S.; Dong, Y.N. Deep learning-based picture identification and classification algorithms are studied and discussed. pp. 274–278 in Proceedings of the 8th–10th November 2019 International Conference on Machine Learning, Big Data, and Business Intelligence (MLBDBI), Taiyuan, China.
[19]. Ronneberger, O.; Fischer, P.; Brox, T. U-net: Convolutional networks for biomedical image segmentation. In the 18th International Conference on Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015, held in Munich,
[20]. Proceedings, Part III 18, Berlin/Heidelberg, Germany, Springer, 2015, pp. 234–241. Germany, October 5–9, 2015.
[21]. Sun, J.; Ren, S.; Zhang, X.; He, K. Identity mappings in deep residual networks. Part IV 14 of the proceedings of the 14th European Conference on Computer Vision (ECCV 2016), held in Amsterdam, The Netherlands, October 11–14, 2016 are available from Springer in Berlin/Heidelberg, Germany, pp. 630–645.
[22]. Pouyanfar, S.; Sadiq, S.; Yan, Y.; Tian, H.; Tao, Y.; Reyes, M.P.; Shyu, M.L.; Chen, S.C.; Iyengar, S.S. An overview of deep learning: Methods, strategies, and uses CSUR (ACM Computing Survey) 2018, 51, 1–36.
[23]. Manzo, C.; Otero-Viñas, M.; Cullell-Dalmau, M. Research methods simplified: Deep learning for the categorization of dermatological pictures. 2020, 140, 507–514, J. Investig. Dermatol.
[24]. Melanoma. Lancet 2018, 392, 971–984. [28] Schadendorf, D.; van Akkooi, A.C.; Berking, C.; Griewank, K.G.; Gutzmer, R.; Hauschild, A.; Stang, A.; Roesch, A.; Ugurel, S.
[25]. Srivastava Swati Sharma, Deepti (2016). Skin Cancer Automatically Detected via Neural Network Classification Engineering and Technical Research International, 4, 1 (2019)