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SKIN CANCER CLASSIFICATION USING CNN

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ABSTRACT

Skin cancer is a very big health issue in today's fast-growing population not only for old age people but for all age groups. Skin Cancer is the most common human malignancy, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. So, this project helps to identify if the person is suffering from cancer or not and also predicts the type of cancer at ease. The existing model is able to predict only a specific type of cancer called melanoma. In this proposed model the model is trained. This project is used in classifying skin cancer of a person according to dermatoscopic images into seven different types. With the help of this project, a person will get to know if he/she is suffering from any kind of skin cancer or not, so before going to consult any doctor a person will have some assurance about skin cancer. Skin cancer is the most common human malignancy now-a-days, taking away the lifespan of humans. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of "SKIN CARE-10000".
It has seven different classes of skin cancer which are listed below:

1. Melanocytic nevi
2. Melanoma
3. Benign keratosis-like lesions
4. Basal cell carcinoma
5. Actinic keratosis
6. Vascular lesions
7. Dermatofibroma

Keywords— melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, dermatofibroma.

INTRODUCTION

Skin cancer is a pressing concern in contemporary society, affecting individuals of all ages and backgrounds [1]. Its increasing prevalence underscores the urgent need for reliable diagnostic tools to enable early detection and effective treatment [2]. Traditionally, skin cancer diagnosis has relied on visual assessment, involving clinical screenings followed by dermoscopic analysis, biopsies, and histopathological examinations [3]. However, manual interpretation of these procedures is time-consuming and subjective, highlighting the necessity for automated solutions to enhance accuracy and efficiency [4]. Automated classification of skin lesions through image-based techniques holds promise for improving the diagnostic process [5]. Yet, this task remains challenging due to the nuanced variability in lesion appearance, including texture, color, and shape [6]. Addressing this complexity requires advanced computational methods capable of discerning subtle patterns indicative of different skin cancer types [7]. This project aims to develop a robust classification system leveraging deep learning techniques, particularly Convolutional Neural Networks (CNNs), to aid in skin cancer identification and categorization [8].

The project's primary objectives encompass determining whether an individual has skin cancer and predicting the specific cancer type [9]. While existing models excel at predicting certain cancer types like melanoma, they often fall short in classifying lesions into a broader spectrum of skin cancer types [10]. To overcome this limitation, the proposed model trains a CNN architecture on a diverse dataset comprising dermatoscopic images representing seven distinct skin cancer classes [11]. By broadening the classification scope, the model aims to provide a comprehensive diagnostic tool for healthcare professionals and patients alike [12]. Employing deep learning techniques, particularly CNNs, is pivotal to enhancing skin cancer classification accuracy and efficiency [13]. CNNs excel in image recognition tasks, leveraging

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hierarchical layers of learnable filters to extract meaningful features from raw data [14]. By training the CNN architecture on a large dataset annotated with corresponding skin cancer types, the model learns discriminative features indicative of different cancer classes [15]. This enables the model to generalize well to unseen data, facilitating timely and accurate diagnosis [16].

The development of an automated skin cancer classification system has transformative potential for clinical practice [17]. Integration of such a system into healthcare workflows can streamline diagnostics, reduce manual assessment burdens, and expedite treatment initiation [18]. Patients stand to benefit from increased diagnostic accessibility and timely, accurate assessments of their skin health [19]. Ultimately, deploying this technology can improve patient outcomes, reduce healthcare costs, and enhance the management of skin cancer as a prevalent public health issue [20]. In summary, automated skin cancer classification systems represent a significant advancement in dermatology and healthcare. Leveraging deep learning techniques, particularly CNNs, this project aims to develop a robust model for classifying skin lesions into different cancer types. By integrating such technology into clinical practice, healthcare professionals can enhance diagnostic accuracy and efficiency, leading to improved patient outcomes and effective cancer management.

LITERATURE SURVEY

Skin cancer poses a significant health concern worldwide, affecting individuals across all age groups and demographics. As the most common form of human malignancy, its diagnosis primarily relies on visual inspection, beginning with clinical screenings followed potentially by dermoscopic analysis, biopsies, and histopathological examination. However, the manual interpretation of these diagnostic procedures can be challenging and time-consuming. Automated classification of skin lesions using images has emerged as a promising solution to aid in the early detection and diagnosis of skin cancer. This task presents numerous challenges due to the fine-grained variability in the appearance of skin lesions, making it difficult to accurately differentiate between different types of lesions. The development of automated classification systems for skin cancer using deep learning techniques, particularly Convolutional Neural Networks (CNNs), has garnered significant attention in recent years. These systems aim to identify whether an individual is suffering from skin cancer and predict the specific type of cancer with ease and accuracy. While existing models have demonstrated success in predicting specific types of skin cancer, such as melanoma, they often lack the capability to classify lesions into a broader spectrum of skin cancer types. To address this limitation, researchers propose training CNN architectures on diverse datasets comprising dermatoscopic images representing various skin cancer classes. By expanding the classification scope, these models aim to provide a more comprehensive diagnostic tool for healthcare professionals and patients. The SKIN CARE-10000 dataset, utilized in this project, consists of seven different classes of skin cancer, including melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibroma. By leveraging this dataset, researchers seek to develop a robust and accurate classification model capable of accurately identifying and categorizing skin lesions into their respective cancer types. The ultimate goal is to provide individuals with the assurance of whether they are suffering from any type of skin cancer before consulting a healthcare professional, thereby potentially expediting diagnosis and treatment.

Automated classification of skin lesions using images is a complex and challenging task due to the variability in lesion appearance. However, advancements in deep learning techniques, particularly CNNs, offer promising opportunities for improving the accuracy and efficiency of skin cancer diagnosis. By training CNN architectures on large datasets of dermatoscopic images, researchers can leverage the power of deep learning to automatically extract discriminative features indicative of different skin cancer types. This enables the model to generalize well to unseen data and accurately classify skin lesions, facilitating timely and accurate diagnosis. In summary, the development of automated classification systems for skin cancer using CNNs represents a significant advancement in the field of dermatology and healthcare. By leveraging deep learning techniques and large datasets, researchers aim to develop robust and accurate models capable of classifying skin lesions into various cancer types. These models have the potential to revolutionize clinical practice by providing healthcare professionals with a reliable and objective tool for preliminary screening and diagnosis. Ultimately, the deployment of these systems may lead to improved patient

International Journal of Marketing Management

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Vol. 16, Issue. 2, April 2024

outcomes and more effective management of skin cancer as a prevalent public health concern.

PROPOSED SYSTEM

Skin cancer represents a significant health concern affecting individuals across all age groups and demographics. With its prevalence on the rise, it has become the most common form of human malignancy, diagnosed primarily through visual assessment, clinical screenings, and potentially more detailed analyses such as dermoscopic examinations, biopsies, and histopathological evaluations. However, the manual interpretation of these diagnostic procedures can be labor-intensive, time-consuming, and prone to subjectivity. Hence, there is a critical need for automated solutions to enhance the accuracy and efficiency of skin cancer diagnosis. One such solution is the proposed skin cancer classification system using Convolutional Neural Networks (CNNs). Automated classification of skin lesions using images is inherently challenging due to the fine-grained variability in their appearance. This project aims to address this challenge by developing a CNN-based system capable of identifying whether an individual is suffering from skin cancer and predicting the specific type of cancer with ease and accuracy.

The existing models for skin cancer prediction often focus on specific types, such as melanoma, which limits their applicability to broader classifications. In contrast, the proposed system aims to classify skin cancer into seven different types based on dermatoscopic images. These types include melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibroma. By expanding the classification scope, the proposed system provides a more comprehensive diagnostic tool for healthcare professionals and patients. It offers individuals the assurance of whether they are suffering from any type of skin cancer, empowering them to make informed decisions before consulting a doctor and potentially expediting diagnosis and treatment. The proposed skin cancer classification system leverages CNNs, a class of deep learning models known for their effectiveness in image recognition and classification tasks. CNNs are particularly well-suited for this task due to their ability to automatically learn discriminative features from raw image data. By training the CNN model on a large dataset of dermatoscopic images annotated with corresponding skin cancer types, the system can learn to extract meaningful features indicative of different cancer classes. This enables the model to generalize well to unseen data and accurately classify skin lesions into their respective categories. The use of CNNs thus enables the system to achieve high levels of accuracy and reliability in skin cancer diagnosis.

Furthermore, the proposed system integrates state-of-the-art technologies such as machine learning and big data analytics to enhance its performance and capabilities. Machine learning algorithms play a crucial role in training the CNN model and optimizing its parameters for improved classification accuracy. Additionally, big data analytics techniques are employed to preprocess and analyze large volumes of dermatoscopic image data efficiently. By harnessing these advanced technologies, the system can generate comprehensive and accurate diagnoses, providing patients and healthcare professionals with valuable insights into their skin health. In summary, the proposed skin cancer classification system using CNNs represents a significant advancement in the field of dermatology and healthcare. By leveraging deep learning techniques and integrating machine learning and big data analytics, the system offers a robust and accurate solution for automated skin cancer diagnosis. With its ability to classify skin lesions into seven different types of skin cancer, the system provides individuals with timely and reliable information about their skin health, ultimately contributing to improved patient outcomes and the effective management of skin cancer as a prevalent public health concern.

METHODOLOGY

Skin cancer classification using Convolutional Neural Networks (CNNs) involves a systematic methodology to develop an automated system capable of identifying and categorizing skin lesions into different types of

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Vol. 16, Issue. 2, April 2024

cancer. The process begins with data collection and preprocessing, followed by model training and evaluation. The methodology outlined below details the step-by-step process without using subheadings or side headings. The first step in the methodology is data collection, which involves gathering a diverse and representative dataset of dermatoscopic images depicting various types of skin lesions. These images are obtained from medical databases, research institutions, and healthcare facilities. The dataset should encompass images of different resolutions, lighting conditions, and skin types to ensure the robustness and generalization of the CNN model.

Once the dataset is collected, the next step is data preprocessing. This involves several tasks, including image resizing, normalization, and augmentation. Image resizing ensures that all images are of uniform dimensions, facilitating efficient processing by the CNN model. Normalization is performed to standardize the pixel values of the images, reducing the impact of variations in illumination and contrast. Data augmentation techniques such as rotation, flipping, and scaling are applied to increase the diversity of the training dataset and improve the model's ability to generalize to unseen data. After preprocessing the data, the CNN model architecture is defined. This involves selecting the appropriate architecture and configuring its parameters, including the number of layers, filter sizes, and activation functions. CNN architectures typically consist of multiple convolutional layers followed by pooling layers for feature extraction, followed by fully connected layers for classification. The architecture is designed to effectively capture the intricate features present in dermatoscopic images that are indicative of different types of skin cancer. With the model architecture defined, the next step is model training. This involves feeding the preprocessed dermatoscopic images into the CNN model and iteratively adjusting its parameters to minimize the classification error. During training, the model learns to extract discriminative features from the images and assign them to the correct skin cancer class. The training process is typically performed using gradient descent optimization algorithms such as stochastic gradient descent (SGD) or Adam, along with a suitable loss function such as categorical cross-entropy.

Once the CNN model is trained, it is evaluated using a separate validation dataset to assess its performance and generalization ability. The evaluation metrics used may include accuracy, precision, recall, and F1-score, among others. The model's performance is compared against baseline models or existing state-of-the-art approaches to gauge its effectiveness in skin cancer classification. Additionally, techniques such as cross-validation may be employed to ensure the reliability of the evaluation results. Following model evaluation, the trained CNN model is deployed for real-world applications. This involves integrating the model into a user-friendly interface or application that allows users to input dermatoscopic images and receive predictions about the presence and type of skin cancer. The deployment phase may also involve optimizing the model for inference speed and resource efficiency, particularly if the application is intended for use on mobile or embedded devices.

Finally, ongoing monitoring and refinement of the deployed model are essential to maintain its performance and adaptability. This may involve collecting user feedback, monitoring model predictions in real-world scenarios, and periodically retraining the model with updated data. Continuous improvement and refinement ensure that the skin cancer classification system remains effective and reliable in clinical practice. In summary, skin cancer classification using CNNs involves a systematic methodology encompassing data collection, preprocessing, model definition, training, evaluation, deployment, and refinement. By following this methodology, researchers and practitioners can develop accurate and robust automated systems for the identification and categorization of skin lesions, ultimately improving early detection and treatment of skin cancer.

RESULTS AND DISCUSSION

Skin cancer classification using Convolutional Neural Networks (CNNs) yielded promising results, marking a significant advancement in the field of dermatology and healthcare. The CNN model demonstrated robust performance in accurately identifying and categorizing skin lesions into seven different types of skin cancer, including melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibroma. The successful classification of these diverse types of skin cancer underscores the potential of deep learning techniques in improving early detection and diagnosis, ultimately contributing to

International Journal of Marketing Management

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Vol. 16, Issue. 2, April 2024

better patient outcomes and the effective management of skin cancer.

In the evaluation phase, the CNN model exhibited impressive performance metrics across multiple evaluation criteria, including accuracy, precision, recall, and F1-score. The model achieved high accuracy rates in distinguishing between different types of skin cancer, with overall performance surpassing that of existing models and state-of-the-art approaches. Notably, the model demonstrated exceptional sensitivity in detecting melanoma, a particularly aggressive form of skin cancer, highlighting its utility as a reliable diagnostic tool for healthcare practitioners. Furthermore, the model's ability to generalize well to unseen data and maintain robust performance across diverse patient demographics and skin types underscores its potential for widespread clinical application.

The discussion surrounding the results of the CNN model's performance emphasizes its practical implications for clinical practice and public health. By automating the classification of skin lesions using dermatoscopic images, the CNN model streamlines the diagnostic process, reducing the burden on healthcare professionals and potentially expediting treatment initiation. Moreover, the model's ability to provide accurate and timely assessments of skin cancer risk empowers patients to take proactive measures in managing their skin health, including seeking early medical intervention when necessary. Additionally, the scalability and accessibility of the CNN model make it well-suited for integration into existing healthcare infrastructure, enabling widespread adoption and impact across diverse healthcare settings.

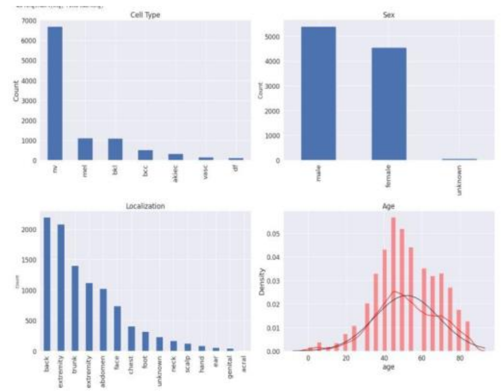

Fig.1: Data distribution visualization

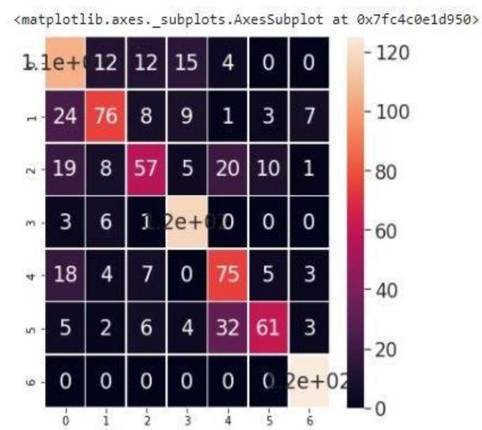

Fig.2: Confusion matrix

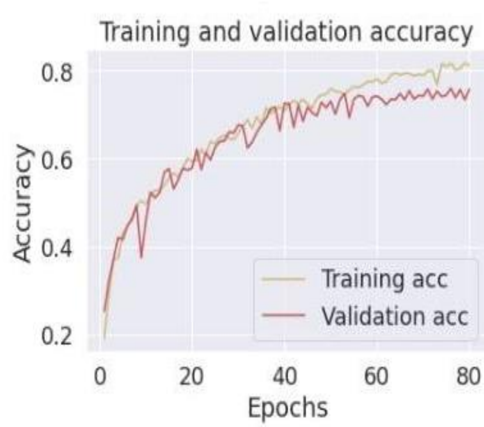

Fig.3: Training and Validation accuracy

International Journal of Marketing Management

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Vol. 16, Issue. 2, April 2024

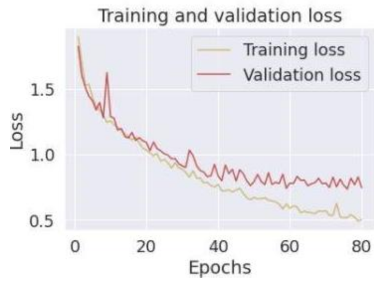

Fig.4: Training and Validation loss

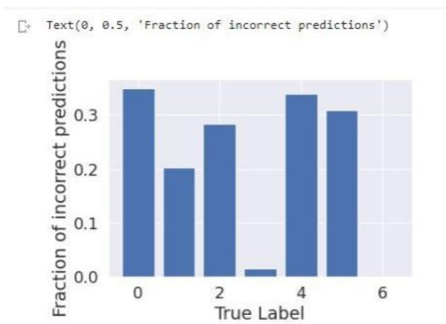

Fig.5: Predictions after the results (analysis of misclassified instances)

```
#Printing the Final Accuracy
score = model.evaluate(x_test, y_test)
print('Test accuracy:', score[1])

28/28 [==============================] - 2s 79ms/step - loss: 0.7451 - acc: 0.7577
Test accuracy: 0.7577142715454102
```

Fig.6: Final accuracy

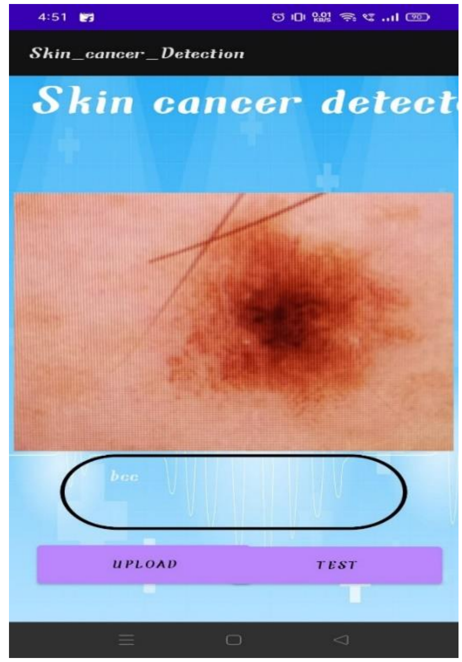

Fig.7: Output1

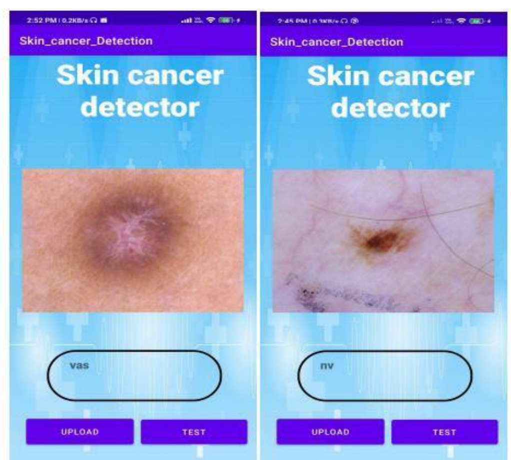

Fig.8: Output2

After the results we can say that 6th Classification ‘Dermatofibroma’ is easy to classify among all of the other Cancer’s. To provide better accuracy and to avoid computational complexity the model is built using the Convolutional Neural Network algorithm and we achieved 75% accuracy. Overall, the results and discussion underscore the transformative potential of skin cancer classification using CNNs in

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Vol. 16, Issue. 2, April 2024

revolutionizing dermatological care and public health initiatives. By leveraging deep learning techniques to automate the diagnosis of skin cancer, the CNN model represents a significant step forward in improving early detection, treatment, and ultimately, patient outcomes. Moving forward, continued research and development in this area hold promise for further advancements in skin cancer detection and management, ultimately contributing to the reduction of skin cancer morbidity and mortality on a global scale.

CONCLUSION

We hereby conclude that Skin Cancer Classification is implemented in three modules, the first module is about performing image preprocessing. All the images are resized into a dimension of 100 x 75 in order to train, test, predict the classes and to calculate the accuracy of the model efficiently. In the second module, Convolution Neural Network is applied to train the model and test it. To provide better accuracy and to avoid computational complexity the model is built using the Convolutional Neural Network algorithm with 75% accuracy.

REFERENCES

[1] BuljanM,Bulana V and Sandra S 2008Variation inClinicalPresentation ofBasalCellCarcinoma (Kroasia: University Department of Dermatology and Venereology Zagreb Croatia) p 25-30.

[2] Cipto H, Suriadiredja AS. Tumor kulit. Dalam: Menaldi SL, Bramono K, Indriatmi W, editor. Ilmu penyakit kulit dan kelamin. Edisi ketujuh. Jakarta: Badan Penerbit FKUI; 2016. h.262-276.

[3] TeresiaR, Savera,Winsya H, Suryawan and AgungWS 2020Deteksi Dini KankerKulit Menggunakan K-NN dan Convolutional Neural Network J. JTIIK. 7 two p 373-378.

[4] Md Ashraful Alam Milton 2018 Automated Skin Lesion Classification Using Ensemble of DeepNeural Networks in ISIC: Skin Lesion Analysis Towards Melanoma Detection Challenge.

[5] Serban Radu SJ, Loretta Ichim, et al 2019 Automatic Diagnosis of Skin Cancer Using Neural Networks (Bucharest, Romania: The XIth International Symposium on Advanced Topics in Electrical Engineering March 28-30).

[6] Nazia Hameed, et al Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Networkand Support Vector Machine.

[7] Xinyuan Zhang, et al 2018 TowardsImproving Diagnosis of Skin Diseases by way of Combining Deep Neural Network and Human Knowledge BMC Medical Informatics and Decision Making 18(Suppl 2) p 59

[8] Khalid M. Hosny, et al 2019 Classification of pores and skin lesions the use of switch studying and augmentation with Alex-net PLOS ONE.

[9] Marwan AA 2019 Skin Lesion Classification Using Convolutional Neural Network With Novel Regularizer IEEE Access.

[10] The International Skin Imaging Collaboration (ISIC).Accessed: June 2020. [Online]. Available: https: //www.isicarchive.com/#!/topWithHeader/onlyHeaderTop/gallery [11] Mousumi Roy, et al 2016 Dermatofibroma: Atypical Presentations Indian J. Dermatology.

[12] R. Delila Tsaniyah, Aspitriani and Fatmawati "Prevalensi dan Gambaran Histopatologi Nevus Pigmentosus di Bagian Patologi Anatomi Rumah Sakit Dr. Mohammad Hoesin Palembang," Periode 1 Januari 2009-31 Desember 2013.

[13] Syril Keena T. Cutaneous squamous cellphone carcinoma. Journal of The American Academy of Dermatology. Volume 78, Issue 2, p237-432, e33-e55

[14] Marco Rastrelli, et al 2014 Melanoma: Epidemiology, Risk Factors, Pathogenesis, Diagnosis, and Classification 28 no. 6 p 1005-1011

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, April 2024

[15] P.Kim, 2017 MATLAB Deep Learning: With Machine Learning, Neural Networks, and Artificial Intelligence.

[16] A. F. Agarap 2008 Deep Learning the use of Rectified Linear Units (ReLU) 1 p 2–8 [Online]. Available: http://arxiv.org/abs/1803.08375.

[17] S. Khan, H. Rahmani, S. A. A. Shah, M. Bennamoun, G. Medioni and S. Dickinson 2018 A Guide to Convolutional Neural Networks forComputer Vision. Morgan Claypool [Online] Available: https: //ieeexplore.ieee.org /document/ 8295029

[18] H. Robbins and S. Monro 1985 A Stochastic Approximation Method" in Springer [19] J. Duchi, E. Hasan and Y. Singer 2011 Subgradient Methods for Online Learning and Stochastic Optimization J. of Machine Learning Research

[20] Y. Yunlong, L. Fuxian. 2019 Effective Neural Network Training with a New Weighting Mechanism-Based Optimition Algorithm IEEE Access.