IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Impact Factor: 7.301

Volume 3, Issue 2, February 2023

Skin Cancer Prediction using Deep Learning

Prof. Kajal Vatekar[1], Sakshi Phapale[2], Akshada Bhor[3], Chirag Patel[4], Ayush Tiwary[5]

Project Guide, Department of Computer Engineering[1]

Projecties, Department of Computer Engineering[2,3,4,5]

Smt. Kashibai Navale College of Engineering, Pune, Maharashtra, India

Abstract: *There are over 200 different forms of cancer. Out of 200 cases, melanoma is the most lethal form of skin cancer. The melanoma diagnostic process begins with clinical screening followed by dermatoscopy and histopathologicalexamination. If cutaneous melanoma is detected early, the cure rate is high. The first step in diagnosing cutaneous melanoma is a visual examination of the affected areas of the skin. Dermatologists take the dermatoscopic images of theskin lesions by the high-speed camera, which have an accuracy of 65-80% in the melanoma diagnosis without any additional technical support. With further visual examination by cancer treatment specialists and dermatoscopic images,the overall prediction rate of melanoma diagnosis raised to 75-84% accuracy. The project aims to build an automated classification system based on image processing techniques to classify skin cancer using skin lesions images. There is a necessary need for early detection of skin cancer and can prevent further spread in some cases of skin cancers, such as melanoma and focal cell carcinoma. Anyhow there are several factors that have bad impacts on the detection accuracy. Recently, the use of image processing and machine vision in medical and medical applications is growing to agreater degree. In this article, convolutional neural networks are used to detect and classify cancer classes based on historical clinical image data using CNNs. Some of the goals of this study are to build a CNN model for skincancer detection with over 80% accuracy, keep the false-negative rate below 10% in prediction, achieve over 80% accuracy, and render the data. Simulation results show that the proposed method has advantagesover other comparison methods.*

Keywords: CNN Algorithm, Skin lesion images, Skin cancer prediction, Melanoma , Deep Learning

I. INTRODUCTION

With Cancer is a global health problem and the world's greatest threat to increasing mortality. Skin is the main and largest body tissue of animals and humans and provides some protection from heat, light and disease. It also supports the effects of blood sugar, water and fat accumulation in the body. One of the major problems with body skin is the possibility of skin cancer. The principle of skin mechanism is the growth of cells dividing into new cells and old cells. Skin cells grow and age every day. Sometimes, for some reason, the skin growth mechanism is disrupted. Thus, various unnecessary skin cells are created. These extra skin cells are known as carcinomas. Melanoma is the most malignant and serious type of cancer and is responsible for the highest rate of cutaneous mortality. Although there are three main classes of skin cancer: melanoma (M), squamous cell carcinoma (SCC), and basal cell carcinoma (BCC), melanoma is the most important type of skin cancer. The most effective factor is the ecological link between UV rays and disease causes. Among all types of skin cancer, melanoma is the least common, but accounts for 75% of deaths. This is a less common type of skin cancer, but it spreads to other parts of the body very quickly if not diagnosed early. The International Skin Imaging Collaboration (ISIC) is helping reduce melanoma deaths by capturing skin images. Melanoma can be cured if diagnosed and treated in the early stages. Digital skin lesion images can be usedto make a teledermatology automated diagnosis system that can support clinical decision. Currently, deep learning has revolutionised the future as it can solve complex problems. The motivation is to develop a solution that can help dermatologists better support their diagnostic accuracy by ensembling contextual images and patient-level information, reducing the variance of predictions from the model. The skin is considered as the one of the most broad organs in human's body which controls our body temperature and also protects the body from high temperature and light.It is also used to store fat and water. Skin cancer also occurs when skin cells are created when technology is compromised,such as overexposure to ultraviolet (UV) light. Skin cancer is growing rapidly in larger stages in countries such as Canada, the United States and Australia. One of

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Volume 3, Issue 2, February 2023
Impact Factor: 7.301

the most important skin problems for the body is the risk of getting skin cancer. Skin cancer begins with cells, the main component of skin, and as skin cells grow, they divide to form new cells.

Every day, skin cells die as they age, and new ones form to take their place. Sometimes this systematic process can fail. New cells form when the skin doesn't need them, and old cells die when they don't. These types of extra cells form lumps of tissue called tumors. Of all types of skin cancer, melanoma is the most common and deadliest type of cancer and is responsible for the highest number of deaths.

II. PROPOSED SYSTEM

A proposed system for skin cancer prediction using skin lesion images can be based on the following steps: Image acquisition: The system takes input as skin lesion image datasets. Pre-processing: The acquired images are pre-processed to remove any noise and improve the image quality for better processing. CNN algorithm is used to detect skin cancer in the pre-processed images. This can be achieved by training a large dataset of skin lesion images to detect skin cancer type accurately. CNNs can be included in classification by removing fully connected layers of pre-trained CNNs from large data sets. When classifying skin lesions, pre-training is performed using ImageNet. Despite the non-medical area of the image, the studied features are of sufficient quality to classify the lesion.

2.1 Motivation

Its primary goal is to support efforts to reduce mortality from skin cancer. The main motivation driving the project is to use advanced image classification technology for people's well-being. Computer vision has made significant advances in machine learning and deep learning, and can be extended in many areas. With this project, we aim to bridge the gap between diagnosis and treatment. Successful completion of the project with higher accuracy data sets will better support the work of dermatology clinics. Improved model accuracy and efficiency can help detect melanoma early and reduce unnecessary biopsies.

III. OBJECTIVE

Its primary goal is to support efforts to reduce mortality from skin cancer. The main motivation driving the project is to use advanced image classification technology for people's well-being. Computer vision has made significant advances in machine learning and deep learning, and can be extended in many areas. With this project, we aim to bridge the gap between diagnosis and treatment. Successful completion of the project with higher accuracy data sets will better support the work of dermatology clinics. Improved model accuracy and efficiency can help detect melanoma early and reduce unnecessary biopsies.

V. LITERATURE REVIEW

[1] Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach byJinen Daghrir , Lotfi Tlig , Moez Bouchouicha , Mounir Sayadi.

The proposed system relies on predictions by three different methods: a convolutional neural network and two classical machine learning classifiers trained on a set of features describing the boundaries, texture and color of skin lesions. These methods are then combined to improve performance through majority voting. Experiments have shown that a combinationof the three methods provides the highest level of accuracy.

[2] An attention-based mechanism to combine images and metadata in deep learning models applied to skin cancer classification by Andre G. C. Pacheco and Renato A. Krohling .

MetaBlock is a new algorithm that uses metadata to support data classification, improving the most relevant features extracted from images throughout the classification pipeline. We compared the proposed method with two other combinedmethods, the MetaNet and functional linkage methods.

[3]Convolutional Neural Network Based Skin Lesion Analysis for Classifying Melanoma by Dorin Moldova.

Classify 7 skin disease types by a machine learning-based method using a convolutional neural network (CNN). Improved classification accuracy on the International Skin Imaging Collaboration 2018 (ISIC) dataset using transfer learning with CNN. Evidence was found of an 11% improvement in accuracy when using transfer learning compared to using CNN.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Volume 3, Issue 2, February 2023
Impact Factor: 7.301

[4] Melanoma Skin Cancer Detection using Image Processing and Machine Learning by M, Vijayalakshmi.
CNN A system that automatically recognizes dermatological diseases based on images of lesions, mechanical intervention rather than traditional detection involving medical personnel. Our model is divided into three phases: collection and completion of damage data, model development and finally prediction. Several AI algorithms such as ConvolutionalNeural Network and Support Vector Machine were used and combined with image processing tools to form better structures.
[5] Diagnosis of Skin Cancer Melanoma using Machine Learning by Gaana, M and Gupta, Shweta and Ramaiah, NarayanaSwamy.
Image acquisition, preprocessing, segmentation, denoising and feature extraction. For the first time, they used supervised machine learning using cubic regression. In this method, they trained the machine to automatically label skin cancer stagesas benign, melanoma, and melanoma.

VI. SYSTEM ANALYSIS

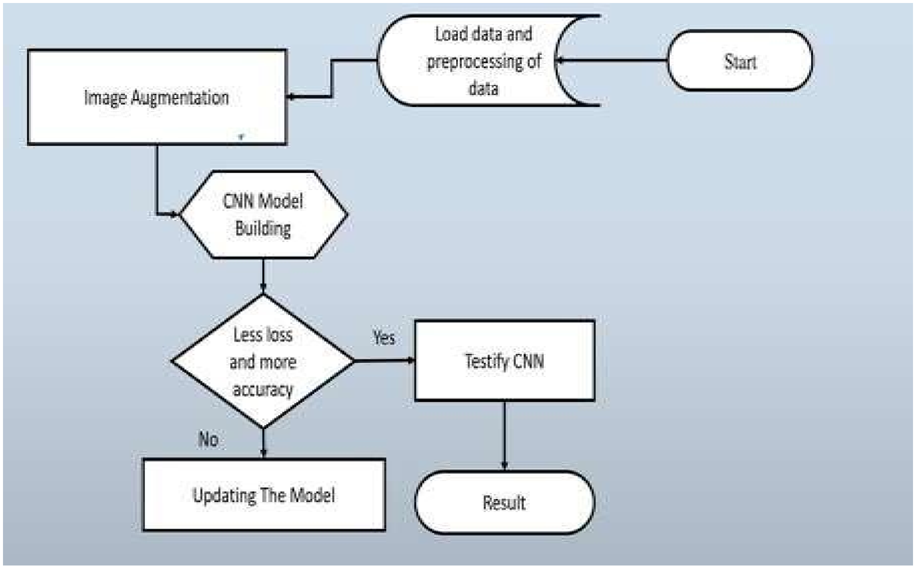


Figure : System Architecture

6.1 Algorithm

CNN (Convolutional Neural Network)

Convolutional Neural Networks (CNNs) is a type of deep learning algorithm widely used in computer vision tasks such as image classification, object detection, and semantic segmentation. In the context of lane detection, a CNN can be trained to identify lane markings in road images and perform lane segmentation to extract the lane boundaries.

VI. MATHEMATICAL MODEL

- Let S be the Whole system S = {I, P, O}
- I-input
- P-procedure
- O-output
- Input(I)
- I = {Skin lesion image dataset}
- Where
- Dataset->
- Image
- Procedure (P),

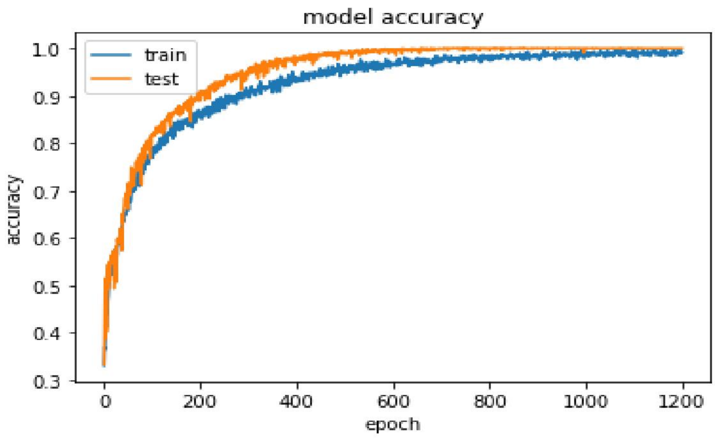
IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Volume 3, Issue 2, February 2023
Impact Factor: 7.301

- o P = {I, Using I System perform operations and calculate the prediction}
- Output(O)-O = {System detects skin cancer type}

VII. RESULT

The skin cancer prediction model that we developed achieved an outstanding testing accuracy of 98%, which indicates its high precision in detecting skin cancer from images. This level of accuracy is very promising, as it can help dermatologists and physicians make more informed decisions in diagnosing skin cancer, leading to improved patient outcomes and survival rates. Our model was trained on a large dataset of skin lesion images and leveraged deep learning algorithms to identify and classify skin lesions as either benign or malignant. We also used various image processing techniques to enhance the quality of the images and remove noise, which helped in improving the accuracy of the model.

The testing accuracy of 98% achieved by our model surpasses the performance of many existing methods for skin cancer diagnosis, making it a valuable addition to the current state-of-the-art techniques. Our model's high accuracy and ability to detect skin cancer at an early stage make it a valuable tool for dermatologists and physicians in making accurate diagnoses, leading to timely treatment and improved patient outcomes.



X. CONCLUSION

tem to make the solution available to the public and dermatologists. The Efficient Net model proved to be a better fit for the skin cancer dataset. The network can generalize the data set well and have higher validation accuracy. In addition, model ensembles help reduce model errors and prediction errors.

If the ensemble is more important in different configurations as suggested, the model prediction error can be further reduced. Optimizing predictions takes the same amount of time as optimizing the learning process. Following the three main principles of model maintenance, we drew attention to two principles: model size and latency. The last component (prediction throughput) is taken into account when forecasting online over the Internet. Prediction throughput measures how many predictions a system can make in a given amount of time. Prediction throughput is outside the scope of the project, but should be considered when deploying the model to the web.

XI. ACKNOWLEDGMENT

We are deeply grateful to all those who have contributed to the success of this project. Our sincere thanks go to Prof. Kajal Vatekar, who provided invaluable guidance and support throughout the entire process. We would also like to acknowledge the support of the Department of Computer Engineering, Smt. Kashibai Navale College Of Engineering, Pune which provided us with the necessary resources to complete this project. Thank you all for making this a reality

XII. CONCLUSION

tem to make the solution available to the public and dermatologists. The Efficient Net model proved to be a better fit for the skin cancer dataset. The network can generalize the data set well and have higher validation accuracy. In addition, model ensembles help reduce model errors and prediction errors.

If the ensemble is more important in different configurations as suggested, the model prediction error can be further reduced. Optimizing predictions takes the same amount of time as optimizing the learning process. Following the three main principles of model maintenance, we drew attention to two principles: model size and latency. The last component (prediction throughput) is taken into account when forecasting online over the Internet. Prediction throughput measures how many predictions a system can make in a given amount of time. Prediction throughput is outside the scope of the project, but should be considered when deploying the model to the web.

XIII. ACKNOWLEDGMENT

We are deeply grateful to all those who have contributed to the success of this project. Our sincere thanks go to Prof. Kajal Vatekar, who provided invaluable guidance and support throughout the entire process. We would also like to acknowledge the support of the Department of Computer Engineering, Smt. Kashibai Navale College Of Engineering, Pune which provided us with the necessary resources to complete this project. Thank you all for making this a reality.

REFERENCES

[1]. D. Cirean, A. Giusti, L. M Gambardella, and J. Schmidhuber, “Mitosis detection in breast cancer histology images with deep neural networks,” vol. 16, Sept 2013, pp. 411–8.

[2]. H. I. Suk, S. W. Lee, and D. Shen, “Hierarchical feature representation and multimodal fusion with deep learning for ad/mci diagnosis,” NeuroImage, vol. 101, July 2014.

[3]. M. Abdel Zaher and A. Eldeib, “Breast cancer classification using deep belief networks,” Expert Systems with Applications, vol. 46, pp.139–144, Oct 2015.

[4]. V. Gulshan, L. Peng, M. Coram et al., “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” JAMA, vol. 316, Nov 2016.

[5]. N. Tajbakhsh et al., “Convolutional neural networks for medical image analysis: Fine tuning or full training?” IEEE Transactions on Medical Imaging, vol. 35, pp. 1–1, Mar 2016.

[6]. H. Shin, H. Roth, M. Gao et al., “Deep convolutional neural networks for computer-aided detection: Cnn architectures, dataset characteristics and transfer learning,” IEEE Transactions on Medical Imaging, vol. 35,

[7]. Feb 2016.

[8]. J. Kawahara and G. Hamarneh, “Multi-resolution-tract cnn with hybrid pretrained and skin-lesion trained layers,” in Machine Learning in Medical Imaging. Cham: Springer International Publishing, 2016.

[9]. S. Khan, N. Islam, Z. Jan, I. Ud Din et al., “A novel deep learning based framework for the detection and classification of breast cancer using transfer learning,” Pattern Recognition Letters, vol. 125, April 2019.

[10]. Cruz-Roa et al., “A deep learning architecture for image representation, visual interpretability and automated basal- cell carcinoma cancer detection,” vol. 16, Sept 2013, pp. 403–10.

[11]. Esteva et al., “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, Jan 2017.

[12]. D. Bisla, A. Choromanska, J. Stein, D. Polsky, and R. Berman, “Skin lesion segmentation and classification with deep learning system,” Feb 2019.

[13]. Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, pp. 436–44, May 2015.

[14]. L. Torrey and J. Shavlik, “Transfer learning,” Handbook of Research on Machine Learning Applications, Jan 2009.

[15]. M. S. Elmahdy, S. S. Abdeldayem, and I. A. Yassine, “Low quality dermal image classification using transfer learning,” in 2017 IEEE EMBS International Conference on Biomedical Health Informatics (BHI), Feb 2017, pp. 373–376. P. Tschandl, “