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Enhancing Early Detection of Melanoma: A Deep Learning Approach for Skin Cancer Prediction

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Abstract— Melanoma, a form of skin cancer, is a substantial global public health threat due to its rising prevalence and the potential for severe outcomes if not promptly identified and managed. Detecting skin cancer lesions in their first stages enhances patient outcomes and decreases mortality rates. The core issue investigated in this research paper is the enduring problem of early skin cancer prediction. In the past, individuals often lacked awareness of their skin cancer condition until it had reached late stages. Consequently, this resulted in delayed diagnoses, which restricted the available treatment options and perhaps led to worse outcomes. This research focuses on finding key attributes and methods in a specialized dataset to effectively differentiate between benign and potentially malignant skin lesions, particularly the implementation of an early-stage skin cancer prediction model. It aims to accurately categorize skin mole pictures as benign or malignant using a Convolutional Neural Network (CNN) model built within the PyTorch framework. The primary aim of this study was to enhance the accuracy and effectiveness of diagnosing skin problems by implementing deep learning algorithms to automate the process of showing such conditions. The model underwent training using 3600 skin mole images sourced from the ISIC-Archive on a GPU RTX 3080. Its outstanding performance is shown by an F1 score of 0.8496 and an accuracy rate of 85%. This research aims to create a predictive model and offer a practical solution that healthcare professionals can readily use for early skin cancer prediction.

Keywords- Deep learning; CNN, PyTorch; early detection; malignancy prediction; skin cancer; automated diagnosis.

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I. INTRODUCTION

Skin cancer is characterized by the uncontrolled proliferation of aberrant cells in the epidermis, which is the outermost layer of the skin [1]. This condition arises from accumulated uncorrected DNA damage, leading to genetic abnormalities [2]. Common skin cancers encompass melanoma (also known as malignant melanoma) as well as non-melanoma skin cancers (NMSCs), which comprise basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) [3]. According to the National Cancer Institute [4] and the American Cancer Society [5], about 1,918,030 instances of cancer will be diagnosed in the United States in 2022, resulting in approximately 5,250 new cases each day. Among these cases, skin cancer would account for 108,480 new cases

and 11,990 fatalities [6]. Annually, there is a global occurrence of around 2 to 3 million cases of non-melanoma skin cancers and 132,000 cases of melanoma skin cancers [7]. Melanoma is the most aggressive form of skin cancer, with the most significant mortality risk [8]. The prevalence of malignant melanoma in white populations often rises as latitude decreases. The most significant documented majority is in Australia, where the yearly rates for women and men are respectively more than 10 and 20 times higher than those in Europe. Since the early 1970s, there has been a substantial rise in the occurrence of malignant melanoma, with an annual average increase of 4% in the United States [1]. Melanoma accounts for 55,500 cancer-related fatalities per year or 0.7% of all cancer deaths [9]. The incidence and death rates of melanoma vary among countries because of differences in ethnic and racial demographics [10]. The incidence of melanoma is about 20 times higher in individuals of White ethnicity compared to those of Black race. In general, the lifetime probability of developing melanoma is around 2.6% (or 1 in 38) for individuals of White ethnicity, 0.1% (1 in 1,000) for those of Black race, and 0.6% (1 in 167) for individuals of Hispanic ethnicity[11]. Approximately 9,500 individuals in the United States receive a skin cancer diagnosis daily, according to estimates [12]. Nevertheless, the ability to forecast skin cancer is paramount for several reasons. First and foremost, the prompt identification of a condition significantly enhances the effectiveness of therapy and enhances the likelihood of a successful intervention. Early skin cancer detection enables healthcare practitioners to swiftly commence suitable treatments, potentially minimizing the necessity for major surgical procedures or invasive interventions [13].

The diagnosis of skin cancer usually depends on the visual examination conducted by dermatologists, a method that is subjective and susceptible to mistakes. However, most of the recent studies did not provide clear information on the size or diversity of the dataset. Pham et al. [14] focused on binary melanoma classification and did not explore the performance of the proposed approach on other types of skin lesions or diseases. Subramanian et al. [15] did not provide insights into the computational requirements or scalability of the CNN-RELM model for handling large volumes of medical image data. Sayed et al. [16] present a novel melanoma prediction model and demonstrate its effectiveness which model performance is not validated. Sanketh et al. [17] did not mention the performance metrics used to evaluate the model's accuracy, sensitivity, specificity, or other relevant measures. This study aims to investigate the integration of different imaging modalities with machine learning algorithms to extract pertinent information and enhance the accuracy of predictions. The integration of imaging technology in tandem with prediction models has the potential to transform the domain of skin cancer diagnosis and screening completely. This project aims to enhance public health activities and raise awareness about skin cancer prevention by researching and building accurate skin cancer prediction models. The findings of this research can be utilized to enlighten people regarding the significance of timely identification, periodic selfexaminations, and embracing sun-safe practices.

Moreover, Ashraf et al. [18] propose a system for classifying skin cancer using a deep convolutional neural network. They compare their approach with the most advanced methods currently available in literature. The study centers on forecasting the occurrence of skin cancer in its first phase to enhance the effectiveness of treatment results. The dataset utilized for testing is gathered from DHQ Hospital Faisalabad, Pakistan. The suggested method attains a classification accuracy of around 93.29%, surpassing the current leading methodologies documented in the literature.

Alsaade et al. [19] explore the creation of a recognition system that employs artificial intelligence algorithms to diagnose melanoma skin lesions. This system combines deep learning and traditional artificial intelligence machine learning algorithms to identify skin cancer accurately. It is divided into two components: a feature-based system and a deep learning system. The feature-based system utilizes techniques such as Local Binary Pattern (LBP) and Grey Level Co-occurrence Matrix (GLCM) to extract texture features from dermoscopy images. The acquired features are further analyzed with an artificial neural network (ANN) technique. The deep learning system utilizes the convolutional neural network (CNN) technique to categorize skin illnesses using pre-trained models like AlexNet and ResNet50. The experimental findings demonstrate that the suggested approach surpasses the most advanced techniques for the PH2 and ISIC 2018 datasets, attaining remarkable levels of accuracy. The performance of the suggested systems is evaluated using standard evaluation measures, including accuracy, specificity, sensitivity, precision, recall, and F-score.

Pham et al. [14] provide a technique to enhance the accuracy of melanoma prediction on a dataset with unbalanced data by rebuilding the suitable CNN structure and optimizing algorithms. The introduction encompasses three important features: a custom loss function, custom mini-batch logic, and fully connected layers. The model's performance is evaluated against 157 dermatologists from 12 university hospitals in Germany. The model surpasses all of them, achieving an area under the curve of 94.4%, a sensitivity of 85.0%, and a specificity of 95.0%. The study centers on categorizing melanoma into binary categories and emphasizes the significance of effectively modifying fully connected layers to learn from a large dataset. Utilizing customized mini-batch logic and a tailored loss function results in exceptional outcomes that surpass human accuracy and the prior cutting-edge performance. The paper further presents a dropout block and a customized loss function for melanoma and nevus pictures, utilizing mean squared error. The suggested loss function is being evaluated in terms of its sensitivity and specificity compared to existing loss functions.

Subramanian. et al. [15] have shown that skin cancer, encompassing Melanoma, Basal, and Squamous types, has garnered heightened scrutiny in recent times as a potentially Computer vision application in fatal disease in humans. medical picture diagnosis has exhibited significant potential, as seen by the success of many existing systems in this domain. Convolutional Neural Networks (CNNs) have found extensive application in multiclass image classification datasets. However, their ability to effectively learn from huge datasets is constrained. Regularized Extreme Learning Machines (RELMs) have the benefit of quick learning and robust generalizability, hence enhancing recognition accuracy promptly. This work presents a new method called CNN-RELM, which combines CNNs with RELMs to improve image classification and attain an accuracy of around 98.6%.

Skin cancer is a problematic ailment that impacts people across all age brackets, with a specific emphasis on older folks. The abnormal or accelerated proliferation of epidermal cells causes skin cancer. It is crucial to distinguish skin cancer from other skin disorders because cancer affects the deeper layers of tissue, while other ailments affect the superficial layer of the skin. The utilization of technology can facilitate the early identification of skin cancer, hence diminishing the expenses and time required for detection. Labde et al. [20] suggested that the Convolutional Neural Network (CNN) provides superior accuracy in predicting and categorizing skin cancer compared to the conventional Support Vector Machine method.

Rosas-Lara et al. [21] present a web prototype utilizing convolutional neural networks to identify melanoma, emphasizing the significance of interdisciplinary collaboration in timely skin cancer identification. The study used the Cross Industry Standard Process for Data Mining (CRISP-DM) as a guiding framework for constructing the web prototype. The authors curated a dataset of 18,000 meticulously selected pictures from the data science community. This dataset was utilized for training and assessing the performance of two distinct learning models: one employing convolutional neural network and the other using Res-Net50. The web application was developed with the waterfall paradigm, which follows a linear and systematic approach to software. The paper concludes by suggesting future work and potential improvements for the developed web prototype.

In this study, Sayed et al. [16] provide a new model for predicting melanoma in imbalanced data. They utilize an optimized version of SqueezeNet, a deep learning architecture, by employing bald eagle search optimization. The suggested model completed evaluation using the ISIC 2020 dataset, which is a substantial dataset that is publicly accessible and specifically designed for the categorization of skin lesions. The primary challenge of the dataset is a significant difference in class distribution, which the study tackles by employing a random over-sampling technique followed by data augmentation. The study presents a combined convolutional neural network architecture and bald eagle search (BES) optimization technique to discover the most effective hyperparameter values for SqueezeNet. The experimental findings demonstrate that the suggested model attained an overall accuracy of 98.37%, specificity of 96.47%, sensitivity of 100%, f-score of 98.40%, and area under the curve of 99%. The suggested model is evaluated against VGG19, GoogleNet, and ResNet50, showcasing its resilience and effectiveness. The article indicates that the suggested model is comparable to the most advanced methods in predicting melanoma.

According to the research conducted by Babar et al. [22], melanoma is the most lethal kind of skin cancer, responsible for around 75% of deaths connected to skin cancer. There is a correlation between solar ultraviolet (UV) radiation and the development of skin cancer. Prompt detection of melanoma in its first stages is essential for immediate intervention. The identification of malignant melanoma involves the utilization of dermoscopic and clinical examination techniques. Utilizing digital image classification for skin lesions is a highly effective approach to identifying melanoma. This research presents computer-assisted techniques for detecting melanoma skin cancer, employing several image-processing technologies. The article outlines diverse image-processing methods to enhance melanoma skin cancer detection.

Waweru et al. [17] suggested that Deep Convolutional Neural Networks (DCNNs) have greatly enhanced the ability to classify skin lesions automatically. This improvement in diagnostic performance is particularly beneficial for individuals with limited access to professionals. Researchers have explored the application of Deep Convolutional Neural Networks (DCNNs) to separate Melanoma regions in dermoscopy pictures automatically. The objective is to develop an online service that may offer probability-based diagnosis for skin lesions to general practitioners and lab techs. This research utilized the HAM10000 public dataset for both training and assessment purposes. By incorporating artificial intelligence (AI) with web-based dermoscopic imaging, we might offer easily accessible techniques for analyzing skin lesions. Automating the study of skin lesions can aid in promptly identifying individuals at high risk and expedite the subsequent diagnostic and treatment process.

Sanketh et al. [23] have demonstrated that skin cancer is the prevailing kind of cancer, exhibiting escalating fatality rates on a global scale. Timely identification of skin cancer dramatically enhances treatment results. Integrating deep learning software with convolutional neural networks (CNN) has demonstrated potential in detecting skin cancer. The paper presents a model that utilizes Convolutional Neural Networks (CNN) and Python packages to classify skin pictures as cancerous or benign. The dataset used for training and testing the model is sourced from the International Skin Imaging Collaboration (ISIC). The model's primary objective is to identify skin cancer in its early stages and decrease the death rate.

However, the aims of this study are outlined as follows:

- a. Our research focuses on identifying key attributes and methods in a specialized dataset to effectively differentiate between benign and potentially malignant skin lesions, particularly in the early stages of skin cancer prediction.
- b. Our approach involves utilizing PyTorch, a deep learning framework, and a Convolutional Neural Network (CNN) architecture to enhance the identification of early-stage skin cancer from dermatoscopic pictures.
- c. Our objective is to improve the accuracy of early cancer prediction by using intelligent computer tools.
- d. Our study validates and evaluates the proposed model, demonstrating its performance on both CPU and GPU for categorizing skin pictures as malignant or benign.
- e. Our study creates a predictive model and offers a solution that healthcare professionals can readily utilize for early skin cancer prediction.

II. MATERIALS AND METHODS

Using benign and malignant pictures, the Convolutional Neural Network (CNN) algorithm and the PyTorch framework have been used to build the suggested deep learning-based approaches. Figure 1. displays the block diagram of the proposed method for identifying skin cancer at an advanced stage.



Fig. 1 Framework of proposed system

A. Dataset

The dataset in this study consists of digital photos of skin lesions, focusing on two types of lesions: benign and malignant. A total of 3600 pictures, or 1800 pictures of each category, are included in the dataset. The skin moles included in the dataset came from the well-known dermatological image resource ISIC-Archive [24]. The dataset aims to capture the varied traits and visual attributes connected to distinct skin disorders. The dataset attempts to preserve a balanced representation by distributing an equal number of samples across all categories, enabling impartial training and assessment of the suggested classification model.

B. Data Preprocessing

Each image within the collection possesses a resolution of 224x224 pixels. The dataset utilized in this study was sourced from the ISIC-Archive, adhering to their prescribed usage norms and restrictions. Before inputting the pictures into the model for classification, a standardized data preparation methodology is implemented on the test images. To utilize a pre-trained model, it is necessary to resize and normalize the input data to conform to the original format on which the network was initially trained. To ensure a consistent input size for the model, the pictures are uniformly resized to a set dimension of 224x224 pixels. This is necessary to accommodate the requirements of the pre-trained model. In addition, the pictures are also turned into tensor representations to aid numerical computations in the model. To put the pixel values within a standardized range, the images are normalized using predetermined mean and standard deviation values of [0.5, 0.5, 0.5].

C. Proposed Model Architecture

CancerCNN is a deep-learning model developed with the PyTorch framework. It is mapped to examine and categorize cancerous cells from medical images. The model architecture comprises numerous convolutional layers with increasing depth, labeled conv1 to conv5. To extract meaningful characteristics from the input pictures, each convolutional layer employs a collection of filters. After every convolutional layer, the LeakyReLU activation function is applied to provide non-linearity and improve the model's capacity to learn intricate patterns. Following the convolutional layers, max-pooling layers are added to down sample the feature maps and save the most crucial information while lowering their spatial dimensions. This assists in capturing the most pertinent information and lowers the computational complexity of the model. A dropout layer is included to prevent overfitting randomly sets a fraction of the input units to zero during training. Figure 2 displays model architecture diagram.



Fig. 2 The Architecture of proposed Convolution Neural Network (CNN) model

This regularization strategy keeps the model from depending too much on any one feature, which enhances the model's ability to be more widely applicable. A fully connected layer in the model called fc1 performs classification using the retrieved features and takes the flattened output of the preceding layers. The features acquired from the convolutional layers are combined and mapped to the anticipated class probabilities by the fully connected layer. To further improve the predictions and offer the final output probabilities for each class, a second fully connected layer, fc2, is added at the end.



Fig. 3 The Transformation of Image Data

D. Data Transformation

Data augmentation approaches are employed for training using the transformations module in PyTorch. To improve the model's capacity to generalize to unknown data, techniques including affine transformations, horizontal flipping, color jittering, random resizing and cropping, and Gaussian blur are applied. The dataset's mean and standard deviation are used to normalize the pictures once they have been transformed into tensors. In Figure 3, the data transformation is displayed.

E. Model Training

The stochastic gradient descent (SGD) optimizer with a learning rate of 0.04 is used to train the model. As the loss criteria, the CrossEntropyLoss function is employed. Training is performed with a batch size of four over several epochs. The training dataset is iterated through the training loop, sending the pictures to the model and computing the loss. Backpropagation is used by the optimizer to update the model's parameters.

F. Early Stopping

Early stopping is implemented to guarantee effective training and prevent overfitting. The F1 score is tracked throughout training, and the training is stopped early if it does not improve after a certain number of epochs (in this case, 5). The model that performs the best and has the highest F1 score is retained for further examination and possible deployment. Epoch 7 in Table 1 has the highest F1 score, 0.8496. Nevertheless, the training is terminated early as the F1 score does not increase during the following five epochs. The topperforming model is preserved, and it comes from Epoch 7.

G. Data Analysis Technique

1) Accuracy: Accuracy is a commonly used metric to evaluate the performance of a classification model. It represents the percentage of correctly predicted observations,

whether they are true or false [25]. The formula to calculate accuracy [26] is:

$$Accuracy = \frac{(True Positives + True Negatives)}{(True Positives + True Negatives + False Positives + False Negatives)} (1)$$

2) Precision: It measures the accuracy of positive predictions made by the model. It is the ratio of true positive predictions to the total predicted positives[27]. The formula to calculate Precision [28] is:

$$Precision = \frac{True Positives}{(True Positives + False Positives)}$$
(2)

3) Recall: It measures the ability of the model to identify all positive instances. It is the ratio of true positive predictions to the total actual positives[30], [31], [32]. The formula to calculate Recall [26] is:

$$Recall = \frac{True Positives}{(True Positives + False Negatives)}$$
(3)

4) F1-score: It is the harmonic mean of precision and recall, providing a balance between the two metrics. It helps evaluate the model's overall performance[31], [32]. The formula to calculate F1-score [28] is:

$$F1 - score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$
 (4)

III. RESULTS AND DISCUSSION

The model was trained using a total of 20 epochs. However, an early stopping criterion based on the F1 score was applied. After 19 epochs, the F1 score did not show any improvement for 5 consecutive epochs, leading to the termination of the training process. The best F1 score achieved by the model was 0.8496, which occurred during the 7th epoch. The attained F1 score is encouraging and showcases the efficacy of the PyTorch Convolutional Neural Network (CNN) in identifying skin cancer. The performance of the suggested model aligns with prior studies in the field, suggesting that it can be regarded as a dependable method for detecting skin cancer.

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-	Test Acc	F1 Score
Loss	(%)	
0.0121	81.97	0.8194
0.0126	80.91	0.8079
0.0118	82.88	0.8285
0.0119	83.18	0.8318
0.0126	81.06	0.8098
0.0122	83.48	0.8348
0.0115	85.00	0.8496
0.0119	83.33	0.8332
0.0111	84.39	0.8438
0.0112	83.79	0.8371
0.0115	84.24	0.8424
0.0110	84.85	0.8484
	$\begin{array}{c} 1032\\ \hline 0.0121\\ 0.0126\\ 0.0118\\ 0.0119\\ 0.0126\\ 0.0122\\ 0.0115\\ 0.0115\\ 0.0119\\ 0.0111\\ 0.0112\\ 0.0115\\ 0.0110\\ \end{array}$	0.0121 81.97 0.0126 80.91 0.0118 82.88 0.0119 83.18 0.0126 81.06 0.0122 83.48 0.0115 85.00 0.0119 83.33 0.0111 84.39 0.0112 83.79 0.0115 84.24 0.0110 84.85

DMANCE

TABLE I

TABLE II CPU MODEL PERFORMANCE

Epoch	Train	Train	Test	Test Acc	F1
	Loss	Acc (%)	Loss	(%)	Score
2/5	0.1370	72.70	0.1109	76.82	0.7680
3/5	0.1197	76.83	0.1421	78.64	0.7840
4/5	0.1257	75.46	0.1010	79.70	0.7957
5/5	0.1131	77.89	0.1525	77.58	0.7721

H. Model Evaluation

Following every training session, the model undergoes evaluation using the test dataset. The evaluation of the model's performance is based on the metrics of test loss, test accuracy, and the F1 score. The F1 score is computed by evaluating the predicted and ground truth labels and assessing the model's overall classification efficacy. We employed the CPU for the model's first training, which took 39 minutes. The model undergoes training for five epochs, and the model that achieves the highest performance is stored for subsequent analysis. The performance of the model is displayed in Table 2.

Following the first training of the model on the CPU, we tried to train the model on the GPU. The duration of the training is 6 minutes and 54 seconds. The model undergoes training for seven epochs, during which the model showing the highest performance is preserved for subsequent examination. Table 1 displays the version of the model. The model exhibits superior performance compared to the model trained on the CPU, with a higher F1 score of 0.8496 and a test accuracy of 85.00\%. Upon achieving the highest F1 score at 14 epochs, the model undergoes an additional 5 epochs of training to assess the potential for further improvement in model performance. Nevertheless, the model's performance remains unchanged, activating the early halting mechanism. Figure 4 displays the loss curve and accuracy curve, which offers more understanding of the training process and the effectiveness of the skin cancer detection model.



Fig. 4 Loss curves of the model

The loss curve illustrates the model's convergence throughout the training period. Initially, the decline in loss is rapid, suggesting that the model is effectively learning and adjusting to the training data. During the progress of the training, the rate of decline gradually decelerates until it ultimately levels off at a plateau. The plateauing of the data indicates that the model has successfully collected most of the pertinent information, and more training is unlikely to result in substantial enhancements in its performance. Conversely, Figure 5 shows the Accuracy curves of the model.

The accuracy curve shows the model's capacity to categorize skin cancer pictures over the epochs accurately. Like the loss curve, the accuracy rapidly increases during the first training phases, suggesting successful learning. Nevertheless, the accuracy curve flattens after a specific threshold, implying that further training yields diminishing benefits. As previously said, the F1 score of 0.8496 shows the model's high efficacy in identifying skin cancer. The strong

F1 score and the convergence of the loss and accuracy curves suggest that the model has effectively captured the underlying patterns and characteristics in the skin images.



Fig. 5 Accuracy curves of the model

I. Model Validation

The validation method is undertaken rigorously to confirm the reliability and generalization capabilities of the Cancer CNN model [33]. It aids in determining the model's capacity to differentiate between benign and malignant tumors, which is crucial for its potential use in medical diagnosis and prognosis. The results obtained from the validation procedure are crucial for accurately reporting and evaluating the model's performance. These findings help us understand if the model suits real-world medical picture categorization tasks. Figure 7 shows Validation of the CancerCNN model on benign images. The validation findings show that our CancerCNN model has a high level of accuracy in categorizing skin pictures as either malignant or benign. The model reaches a perfect accuracy of 100% on malignant pictures and a high accuracy of 90% on benign ones. The model's high accuracy showcases its efficacy in distinguishing between malignant and benign tumors, a crucial factor for its prospective use in medical diagnosis and prognosis.

IV. CONCLUSION

This paper focused on improving the accuracy and efficiency of diagnosis by automating the identification of skin disorders using deep learning techniques. To correctly classify skin mole pictures as benign or malignant, this study used a Convolutional Neural Network (CNN) model constructed inside the PyTorch framework. This paper shows how a CNN model may be effectively applied to show benign and malignant skin moles automatically and how deep learning may be used to dramatically improve the accuracy and efficiency of skin cancer diagnosis using AI-driven models [33, 34]. CNN's impressive advancement in the medical area proves the potential of integrating cutting-edge technology, as demonstrated by its capacity to identify complex elements inside pictures. The findings of this study have broad ramifications for dermatology-related medical treatments. We advance diagnostic tools by proving the capacity of AI-driven models to identify malignant cases correctly. Early diagnosis and intervention might result from this, which could eventually improve patient outcomes and perhaps save lives. Our model was trained on 3600 skin mole pictures on a GPU RTX 3080, and its F1 score of 0.8496 and

accuracy of 85% demonstrate its outstanding performance. We show that our suggested approach outperforms certain current state-of-the-art.

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REFERENCES

- World Health Organisation, "Radiation: Ultraviolet (UV) radiation and skin cancer," Radiation: Ultraviolet (UV) radiation and skin cancer 16 October 2017 | Q&A. Accessed: Oct. 20, 2024. [Online]. Available: https://www.who.int/news-room/questions-andanswers/item/radiation-ultraviolet-(uv)-radiation-and-skin-cancer
- [2] "Skin Cancer Information The Skin Cancer Foundation." Accessed: Oct. 20, 2024. [Online]. Available: https://www.skincancer.org/skincancer-information/
- [3] Robinmarksm B B S, "An Overview of Skin Cancers Incidence and Causation", doi: 10.1002/1097-0142(19950115)75:2.
- [4] "Skin Cancer (Including Melanoma)—Patient Version NCI." Accessed: Oct. 20, 2024. [Online]. Available: https://www.cancer.gov/types/skin
- [5] "Information and Resources about Cancer: Breast, Colon, Lung, Prostate, Skin | American Cancer Society." Accessed: Oct. 20, 2024. [Online]. Available: https://www.cancer.org/
- [6] S. Khattar and R. Kaur, "Computer assisted diagnosis of skin cancer: A survey and future recommendations," Computers and Electrical Engineering, vol. 104, p. 108431, Dec. 2022, doi:10.1016/j.compeleceng.2022.108431.
- [7] "Skin Cancer Cancer Center.ai AI i Platform in Oncology and Pathology." Accessed: Oct. 20, 2024. [Online]. Available: https://cancercenter.ai/skin-cancer/
- [8] C. Fortes et al., "A protective effect of the Mediterranean diet for cutaneous melanoma," International Journal of Epidemiology, vol. 37, no. 5, pp. 1018–1029, Jul. 2008, doi: 10.1093/ije/dyn132.
- [9] S. Wróbel, M. Przybyło, and E. Stępień, "The Clinical Trial Landscape for Melanoma Therapies," Journal of Clinical Medicine, vol. 8, no. 3, p. 368, Mar. 2019, doi: 10.3390/jcm8030368.
- [10] D. Schadendorf et al., "Melanoma," The Lancet, vol. 392, no. 10151, pp. 971–984, Sep. 2018, doi: 10.1016/s0140-6736(18)31559-9.
- [11] "Melanoma Skin Cancer Statistics | American Cancer Society." Accessed: Oct. 20, 2024. [Online]. Available: https://www.cancer.org/cancer/types/melanoma-skincancer/about/key-statistics.html
- [12] M. A. O'Leary and S. J. Wang, "Epidemiology and Prevention of Cutaneous Cancer," Otolaryngologic Clinics of North America, vol. 54, no. 2, pp. 247–257, Apr. 2021, doi: 10.1016/j.otc.2020.11.001.
- [13] T. Petrie, R. Samatham, A. M. Witkowski, A. Esteva, and S. A. Leachman, "Melanoma Early Detection: Big Data, Bigger Picture," Journal of Investigative Dermatology, vol. 139, no. 1, pp. 25–30, Jan. 2019, doi: 10.1016/j.jid.2018.06.187.
- [14] T.-C. Pham, C.-M. Luong, V.-D. Hoang, and A. Doucet, "AI outperformed every dermatologist in dermoscopic melanoma diagnosis, using an optimized deep-CNN architecture with custom mini-batch logic and loss function," Scientific Reports, vol. 11, no. 1, Sep. 2021, doi: 10.1038/s41598-021-96707-8.
- [15] Subramanian. M, Md. A. Ala Walid, Dr. Sarada Prasanna Mallick, R. Rastogi, A. Chauhan, and A. Vidya, "Melanoma Skin Cancer Detection using a CNN-Regularized Extreme Learning Machine (RELM) based Model," 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), pp. 1239–1245, Mar. 2023, doi: 10.1109/icears56392.2023.10085489.
- [16] G. I. Sayed, M. M. Soliman, and A. E. Hassanien, "A novel melanoma prediction model for imbalanced data using optimized SqueezeNet by bald eagle search optimization," Computers in Biology and Medicine, vol. 136, p. 104712, Sep. 2021, doi:10.1016/j.compbiomed.2021.104712.
- [17] A. K. Waweru, K. Ahmed, Y. Miao, and P. Kawan, "Deep Learning in Skin Lesion Analysis Towards Cancer Detection," 2020 24th International Conference Information Visualisation (IV), pp. 740–745, Sep. 2020, doi: 10.1109/iv51561.2020.00130.
- [18] R. Ashraf, I. Kiran, T. Mahmood, A. Ur Rehman Butt, N. Razzaq, and Z. Farooq, "An efficient technique for skin cancer classification using deep learning," 2020 IEEE 23rd International Multitopic Conference (INMIC), pp. 1–5, Nov. 2020, doi:10.1109/inmic50486.2020.9318164.

- [19] F. W. Alsaade, T. H. H. Aldhyani, and M. H. Al-Adhaileh, "Developing a Recognition System for Diagnosing Melanoma Skin Lesions Using Artificial Intelligence Algorithms," Computational and Mathematical Methods in Medicine, vol. 2021, pp. 1–20, May 2021, doi: 10.1155/2021/9998379.
- [20] S. Labde and N. Vanjari, "Prediction of Skin Cancer Using CNN," 2022 3rd International Conference for Emerging Technology (INCET), pp. 1–4, May 2022, doi: 10.1109/incet54531.2022.9825093.
- [21] M. Rosas-Lara, J. C. Mendoza-Tello, A. Flores, and G. Zumba-Acosta, "A Convolutional Neural Network-Based Web Prototype to Support Melanoma Skin Cancer Detection," 2022 Third International Conference on Information Systems and Software Technologies (ICI2ST), pp. 1–7, Nov. 2022, doi: 10.1109/ici2st57350.2022.00008.
- [22] M. Babar, R. T. Butt, H. Batool, M. A. Asghar, A. R. Majeed, and M. J. Khan, "A Refined Approach for Classification and Detection of Melanoma Skin Cancer using Deep Neural Network," 2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2), pp. 1–6, May 2021, doi:10.1109/icodt252288.2021.9441520.
- [23] R. S. Sanketh, M. Madhu Bala, P. V. Narendra Reddy, and G. V. S. Phani Kumar, "Melanoma Disease Detection Using Convolutional Neural Networks," 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1031–1037, May 2020, doi: 10.1109/iciccs48265.2020.9121075.
- [24] "ISIC | International Skin Imaging Collaboration." Accessed: Oct. 20, 2024. [Online]. Available: https://www.isic-archive.com/
- [25] N. Fahad, K. O. M. Goh, Md. I. Hossen, C. Tee, and Md. A. Ali, "Building a Fortress Against Fake News," Journal of Telecommunications and the Digital Economy, vol. 11, no. 3, pp. 68– 83, Sep. 2023, doi: 10.18080/jtde.v11n3.765.
- [26] K. Tanvir *et al.*, "Enhancing Early-Stage Detection of Melanoma using a Hybrid BiTDense," *TWIST*, vol. 19, no. 2, pp. 298–305, May 2024, doi: 10.5281/ZENODO.10049652.
- [27] E. Mahamud, N. Fahad, M. Assaduzzaman, S. M. Zain, K. O. M. Goh, and Md. K. Morol, "An explainable artificial intelligence model for

multiple lung diseases classification from chest X-ray images using fine-tuned transfer learning," Decision Analytics Journal, vol. 12, p. 100499, Sep. 2024, doi: 10.1016/j.dajour.2024.100499.

- [28] Md. N. Hossain, N. Fahad, R. Ahmed, A. Sen, Md. S. Al Huda, and Md. I. Hossen, "Preventing Student's Mental Health Problems with the Help of Data Mining," International Journal of Computing, pp. 101–108, Apr. 2024, doi: 10.47839/ijc.23.1.3441.
- [29] Md. A. Ali, Md. K. Morol, M. F. Mridha, N. Fahad, M. S. A. Huda, and N. Ahmed, "Exploring a Novel Machine Learning Approach for Evaluating Parkinson's Disease, Duration, and Vitamin D Level," International Journal of Advanced Computer Science and Applications, vol. 14, no. 12, 2023, doi:10.14569/ijacsa.2023.0141265.
- [30] R. Ahmed et al., "A novel integrated logistic regression model enhanced with recursive feature elimination and explainable artificial intelligence for dementia prediction," Healthcare Analytics, vol. 6, p. 100362, Dec. 2024, doi: 10.1016/j.health.2024.100362.
- [31] N. Fahad, A. Sen, S. S. Jisha, S. Ahmad, H. Mokhlis, and M. S. Hossain, "Identification of Human Movement Through a Novel Machine Learning Approach," 2023 Innovations in Power and Advanced Computing Technologies (i-PACT), pp. 1–5, Dec. 2023, doi:10.1109/i-pact58649.2023.10434296.
- [32] N. Fahad et al., "Stand up Against Bad Intended News: An Approach to Detect Fake News using Machine Learning," Emerging Science Journal, vol. 7, no. 4, pp. 1247–1259, Jul. 2023, doi: 10.28991/esj-2023-07-04-015.
- [33] C. C. Chai, W. H. Khoh, Y. H. Pang, and H. Y. Yap, "A Lung Cancer Detection with Pre-Trained CNN Models," Journal of Informatics and Web Engineering, vol. 3, no. 1, pp. 41–54, Feb. 2024, doi:10.33093/jiwe.2024.3.1.3.
- [34] Y. H. Gan, S. Y. Ooi, Y. H. Pang, Y. H. Tay, and Q. F. Yeo, "Facial Skin Analysis in Malaysians using YOLOv5: A Deep Learning Perspective," Journal of Informatics and Web Engineering, vol. 3, no. 2, pp. 1–18, Jun. 2024, doi: 10.33093/jiwe.2023.3.2.1.