Integration of Multimodal Data Sources for Enhanced Skin Disease Classification and Cancer Prediction: A Study Leveraging Pre-Trained Models on HAM_10000 Metadata and Squamous Cell Carcinoma (SCC) Images.

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Research Article

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Posted Date: January 31st, 2024

DOI: https://doi.org/10.21203/rs.3.rs-3892933/v2

Additional Declarations: The authors declare no competing interests.

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Abstract—: **Skin diseases, disorders, and deficiencies are fundamental issues in the human body. Over the last few decades, they have become widely prevalent, often leading to cancer. This spectrum of ailments ranges from benign conditions to potentially life-threatening cancers, posing significant challenges to global health. Accurate classification of these diseases and timely prediction of malignant transformations are crucial for effective diagnosis and treatment planning. In our research paper, we propose an innovative approach that levitation multimodal data integration to enhance the precision of skin disease classification and improve the prediction of cancerous transformations. The study utilizes the HAM_10000 Metadata, a dataset comprising diverse skin lesions, along with 100 high-resolution images of Squamous Cell Carcinoma (SCC). Pre-trained models, specifically multi-model CNNs, are employed to extract intricate patterns and features. By amalgamating information from these heterogeneous sources and implementing advanced machine learning techniques, the results highlight the effectiveness of this integrative methodology. This approach can revolutionize the fields of dermatology and oncology by providing patients with skin diseases accurate, efficient, and early diagnoses of skin disease. Through this method, it was discovered that SCC images might hold a higher priority for skin cancer identification, achieving an accuracy rate of 92% on the original dataset.**

Keywords— Medical imaging; skin cancer; deep learning; HAM_dataset; Squamous Cell Carcinoma (SCC).

I. INTRODUCTION

The strategic utilization of artificial intelligence (AI) methods has led to substantial improvements in various sectors, including commerce, medical services, farming, online networking, safety, advanced transportation, logistics, environmentally-friendly urban planning, and numerous other intelligent applications[1][2].Convolutional Neural Networks (CNNs) have found extensive applications in the classification of skin lesions. Recent progress in machine learning algorithms has significantly reduced misclassification rates when compared to manual categorization by dermatologists[3]. Basically we wants to explore the utilization of big (images) data to enhance precise dermatological diagnosis services[3], employing diverse CNN architectures to classify various skin cancer types[3]. Despite the advantages of deep learning and pre trained multimodal learning techniques over conventional methods & techniques, they have various limitations and the potential of incorrect pattern identification in certain situations. Traditionally, hereditary skin cancer disorder conditions have been classified based on visible, microscopic, and electron microscope observations[4]. Distinguishing specific subtypes of ichthyoses, a group of genetic skin disorders, often relies on identifying enzyme deficiencies. For skin disease now we have various advances methods in laser technology and photonics-based medical technologies that have significantly accelerated and refined the identification of skin diseases. However, these diagnostic methods remain costly. Initially, an automated dermatology screening system is developed using image processing algorithms, greatly enhancing the classification of skin diseases through feature extraction. However , In this work we focus skin cancer prediction with image dataset of Squamous Cell Carcinoma (SCC) Images[4].Scc is a type of skin infection disease that mainly cause Non-melanoma skin cancer (NMSC), according to national institute of health Dec 2022[4].

In the field of healthcare, artificial intelligence (AI) technology is making significant strides, especially in medical imaging[3]. AI-powered computer programs can assist doctors in diagnosing diseases, including skin cancer, by analyzing images from various medical tests such as CT scans, MRI, and ultrasound. Specifically, techniques like dermoscopy, which allows detailed visualization of skin lesions, are essential for accurate risk assessment in dermatology. Studies have shown that AI algorithms can outperform human clinicians in detecting diseases through medical imaging, marking a significant advancement in healthcare[5].

In other words, we can say that advanced technology like deep learning is now being used to detect various types of cancer, including brain tumors, breast cancer, lung cancer, esophageal cancer, and skin lesions on the feet. Doctors use imaging methods like dermoscopy[6], CT scans, HRCT scans, and MRI to diagnose cancer and gather information about skin cancer in patients worldwide[7]. To make this technology work, fast internet, powerful computers, and reliable online storage are needed to collect and share skin cancer data. These AI solutions can be used on different computers and systems, turning them into advanced medical tools. Normally, a skilled skin doctor examines patients' skin first, and then uses special tools like dermoscopy and sometimes a biopsy. However, this process takes a lot of time, which can cause patients' conditions to worsen[8].

Data scientists mostly use the HAM1000 dataset to training and testing machine learning models for automatic skin lesion classification/prediction, helping in the early detection of skin diseases such as melanoma[6][1]. Melanoma is one of the types of skin cancer, and used to early detection greatly improves the chances of successful treatment. Rest of the paper is organized as follows: Section II- Related work, in this section we mainly focus and introduce related work that was already completed in the field of skin disease for cancer diagnosis. Section III-Proposed Methodology, further in the section, our proposed system has been defined how workflow is going on with dataset to prediction of skin cancer disease. Section IV-Experimental Evaluation, In the experimental section, we work on the technical evaluation of every aspect of the proposed system. Section V-Results and Discussion, this section mainly focuses on outputs and results that come after the testing and training of a model. Also discussed was the performance of our proposed system as compared to previous work done by others.

II. RELATED WORK

Skin cancer-related work was done by various authors and industry-related projects but it still research is going all[9]. In computer vision, digital image processing plays a vital role in analyzing and interpreting images for skin cancer prediction [8]. However, various skin cancer-related works have been proposed in this field. Some of the most important research papers are reviewed in this section, Popescu and colleagues et al. introduced a system that combines deep learning techniques and collective intelligence [9]. They utilized different Convolutional Neural Network (CNN) models on the HAM10000 dataset, which is designed to distinguish various skin lesions, including melanoma [10]. The researchers examined different CNN models, maintaining a weight matrix where the elements were derived from neural network lesion classes[2]. As a result of their analysis, the accuracy of their system improved by approximately three percent. Srinivasu and colleagues et al. introduced a deep learning model for skin disease detection, which combined MobileNet and long short-term memory (LSTM) models [9]–[11]. This hybrid approach was designed to analyze skin diseases effectively. The authors evaluated the performance of their model to assess disease progression and compared its results with other advanced models like fine-tuned neural networks and CNNs. Their hybrid model demonstrated an accuracy of 85% when tested on the HAM10000 dataset [1] [3]. Khan et al. [12] introduced a deep learning model specifically designed for screening skin disease lesions effectively[10], [11]. They conducted experiments utilizing a mask recurrent neural network (MASK-RNN) and combined it with a pyramid network using ResNet50 to extract and classify features with a SoftMax classifier [10], [12]. Their proposed method demonstrated efficient and effective performance when tested on the HAM10000 dataset. Huang and colleagues et al. [13], introduced a lightweight skin cancer detection system designed to assist first-line medical care using deep learning techniques. They utilized the HAM10000 dermoscopy dataset to train their multiclass classification model. Their proposed framework achieved an accuracy rate of 85.8% in accurately identifying skin cancer cases [13]. Khan and colleagues et al. [12][14] proposed a method for classifying skin lesions into multiple categories. They utilized local color-controlled histogram intensity values (LCcHIVs) and applied a novel deep saliency segmentation technique, which involved a ten-layer CNN. A heat map was generated and converted into a binary image using thresholding. To select effective features and avoid dimensionality issues, they employed an improved moth flame optimization algorithm. These features were then used in conjunction with multiple maximum correlation analyses and classified using a kernel extreme learning machine (KELM) classifier [14], [15]. The authors evaluated the classification performance on the HAM10000 dataset, achieving an impressive accuracy rate of 90.67%. Karl and Enrique et al. [16] developed a framework for identifying skin cancer, where they applied transfer learning to a convolutional neural network. This approach was used for both plain and hierarchical classification, enabling them to distinguish between seven different types of skin lesions. Andronescu and colleagues et al. developed a model for skin cancer identification based on dermatoscopic images [16]. They employed a Convolutional Neural Network (CNN) to detect images and patterns, working through three stages: a convolutional layer, a pooling layer, and a fully connected layer. They used the HAM10000 dataset, which consisted of 10,015 images showcasing seven different skin lesions [10], [16], [17]. The images were resized to 90 X 120 pixels and normalized. The dataset was divided into training, test, and validation sets. The CNN was configured with a 3 X 3 kernel size and one stride. An activation function called Rectified Linear Unit (ReLU) was used, and max pooling with a size of 2 X 2 was applied to each layer [3]. However, we found that there are various limitations still under progress such as generalization [3] and Diversity in SCC Images, Imbalances in the distribution of different skin disease classes within the dataset, including SCC images, can impact the model's performance [8]. If certain classes are overrepresented or underrepresented, it may lead to biased predictions.

III. PROPOSED METHODOLOGY

In this paper we propose an intelligent system or model designed to diagnose a variety of skin diseases, including Atopic Dermatitis, Basal Cell Carcinoma, Benign Keratosis-like Lesions, Eczema, Melanocytic Nevi, Melanoma, Psoriasis, Seborrheic Keratoses, Tinea Ringworm, Warts, Molluscum[3].Firstly when we design our system various questions come to existence that is how this system is different from other existing methods or system. So, we found that other system was working only singleton data driven method for skin cancer prediction and their accuracy was low still in single modality. Our proposed system is working with multimodality that is define in Figure 1. Basically, we design a model that contain HAM10000+100 SCC images for prediction of skin cancer with deep neural networks which as illustrated in Figure 1. With this dataset consist of Text files that store information about each image as a text with attributes name like cell-type, gender, affected area, size of image, name of image, age of patient etc. ANN is applied to integrate multimodality with text data and image dataset[5][3]. In dataset images are further resized in the new size of (100, 125, 3), after resizing of images it will take less time for process in our proposed model.

Further, we apply exploratory data analysis that can help detect obvious errors, identify outliers in datasets, understand relationships, unearth important factors, and find patterns within dataset. We apply data augmentation using ImageDataGenerator in python with tensor flow library. ImageDataGenerator generates augmentation of images in real-time that means while the model is still training other images. Internally model can apply any random transformations on each training image as it is passed to the model. Our model contains various layers Conv2D, Maxpool2D, Dropout, and Flatten and dense with activation function ReLU + SoftMax, image shape (100, 125, and 3)[12]. A predefine neural network is implemented first with the sequential model with two dense and dropout layers to get patterns in images. In next

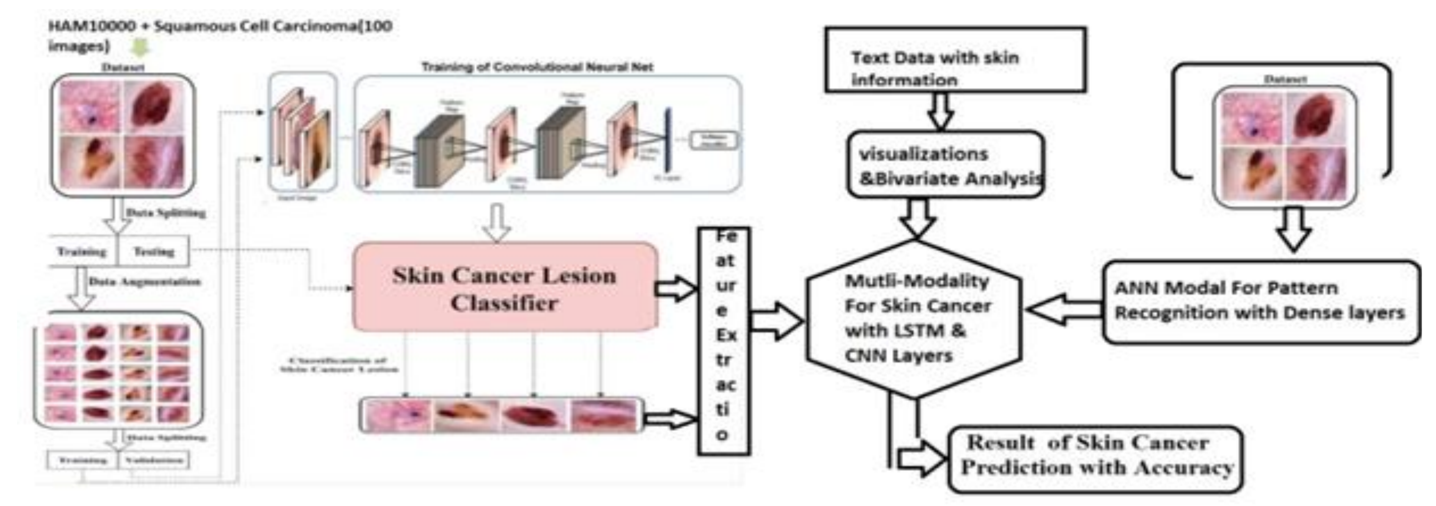

Fig 1. Multi-modality System with LSTM and CNN.

step we implementation training and testing (test size=0.25) with train_test_split function for features extraction and random_state. All images are then converted into binary data set with one hot encoding on the labels, number of classes have 8. Sequential model was implemented with dense layers and activation function RELU and SoftMax with learning rate (0.00075). Optimizer used Adam with learning rate 0.0001 then compiles the model for loss and accuracy matrixes. The accuracy achieved is approximately 71.75 % with epochs 50 and batch size 33 in single model. Further we apply CNN for finding patterns in images to recognize objects, classes, and categories[13].
We start training and testing of CNN model with data augmentation to prevent over fitting. Implementation of

Algorithm for Multimodal Model (**Proposed Model)**

1. Data Preprocessing:
   - Load and preprocess image data.
   - Tokenize and padding text data.
   - Prepare corresponding labels for the dataset.

2. Define Model Architecture:
   - Define input layers for image and text modalities.
   - Implement image processing using a CNN.
   - Implement text processing using an LSTM.
   - Concatenate the outputs of the CNN and LSTM.
   - Add fully connected layers for multimodal fusion.
   - Add an output layer for classification.

3. Compile the Model:
- Specify the optimizer, loss function, and evaluation metrics.
  - Compile the model using the `compile` method.
4. Data Splitting:
   - Split the dataset into training and validation sets.

5. Training:
   - Train the model using the training dataset.
- Use the `fit` method to perform model training.
   - Monitor training and validation loss during epochs.

6. Evaluation:
   - Evaluate the model on the validation dataset.
   - Assess performance metrics such as accuracy, precision, recall, and F1 score.

End of Algorithm

Table 1: - Algorithm for Proposed Model

Model fitting was done with epochs 150 and batch size 16, Accuracy was achieved around 75%.
Further, the prediction was done using integrated text and image data. In this we make our own model that contains total 10 layers. with 2 input layer, 1 conv2D ,1Maxpooling2D, 1 embedding, 1 Flatten ,1 LSTM (64 filters), 1 Concatenate (Flatten+LSTM) and 2 Dense layers (128 + 20 filters). This model was working effectively and efficiently with their design or proposed requirements. Implementation of Model fitting was done with epochs 60 and batch size 16, Accuracy was achieved around 92%.

IV. EXPERIMENTAL-EVALUATION:

Experimental work was conducted on machine with 25 GB of RAM and Tensor flow 2.14.0 installed. The HAM1000 dataset is a collection of high-quality images of common skin lesions that is widely used in the field of dermatology and artificial intelligence research[1], [14]. It consists of 10000 dermoscopy images, including various types of benign and malignant skin lesions. The dataset is valuable for developing and testing algorithms related to skin lesion classification and diagnosis[5].Further we add 100 images of SCC (**Squamous Cell Carcinoma)** that is our own collected data set that we have combined with HAM1000 data set, so this is our new data set represented image shown in figure.2 that contains around 10115 skin images.

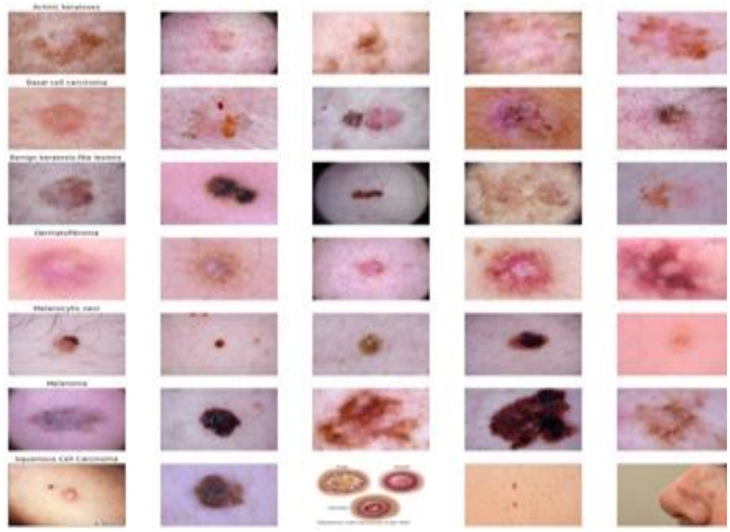

Fig. 2 - HAM_New data set with sample size and class.

V. DATA BALANCING

We utilized the HAM10000 dataset and an additional 100 SCC images, which were primarily associated with its susceptibility to highly imbalanced issues. The challenge of imbalanced data arises when training a deep learning model for complex tasks [5]. This imbalanced dataset often leads to a biased or skewed prediction, impacting the model's performance [17] [19] [20]. Employing data augmentation becomes crucial as it can augment the sample size for these imbalanced classes, thereby creating a more balanced dataset. The effectiveness of a supervised deep learning model's predictions depends on the diversity and size of the training dataset. Data balancing is compulsory for achieving high performance to solve the problem of complex image classification tasks. DataImageGenerator function was used for dataset augmentation [21]. The result of data balancing is shown in Figure 3.

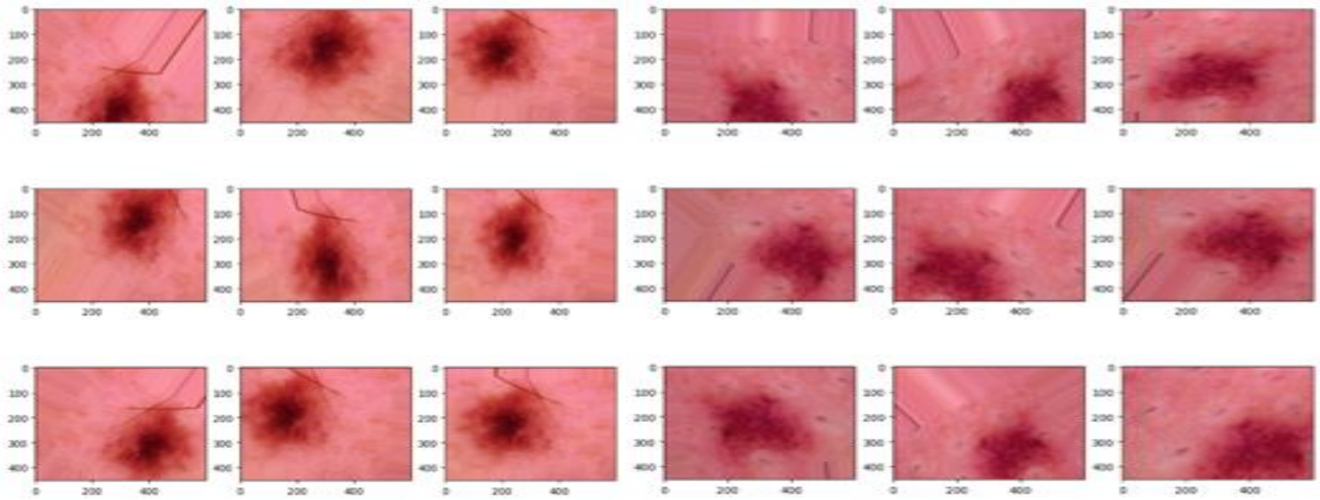

Fig 3. Data augmentation process with images.

We are using data augmentation process to increase the size of data set for batter use of image separation for training and testing of each class. It was done with the help of random process that consist of cropping, flipping the images as horizontally and rotation them at each angle that was possible. After this we collected our own new dataset that consist around 10115 images with multiple of data augmentation process. Further we apply our proposed model for accuracy training and testing tasks.

Table 2: - Skin Dataset with name and percentage of images

Serial No.	Types of skin with name and code	Overall Percentage in Dataset
1	'nv': 'Melanocytic nevi',	66.6 %
2	'mel': 'Melanoma',	11.2 %
3	'bkl': 'Benign keratosis-like lesions ',	10.8 %
4	'bcc': 'Basal cell carcinoma',	5.2 %
5	'akiec': 'Actinic keratoses',	3.3 %
6	'vasc': 'Vascular lesions',	1.4 %
7	'df': 'Dermatofibroma',	1.2 %
8	'scc':'Squamous Cell Carcinoma'	0.5 %

VI. RESULTS AND DISCUSSION

Firstly, we perform the basic analysis on CSV file and dataset (images) that used ANN model. Various Exploratory data analysis as shown Figure 5. where data gives the basic information about the age at which the patient gets affected.

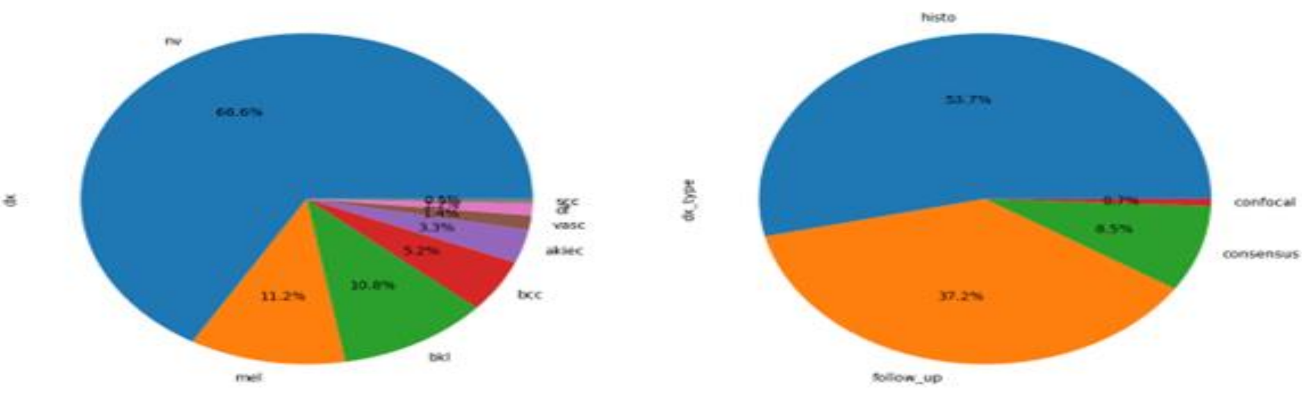

Fig. 4 –Types of images (in percentage) for skin disease prediction.

Results of this research shown that the patients having age from 42-50 years were found most affected. Our results shows that mostly 42-50 years old patients were affected. We also find that male gender cell_type is Cause for skin cancer with various types of skin images. After that we analyzed the type of skin images in our data set. We get perfect information about each type of image shown in figure 4 and table 2. In the second stage of training and testing of SCC images which is now known as HAM_New data set with eight classes of skin lesions.

The model was trained and tested on the dataset that contain 10115(HAM_New) images. Out of that 75% were used for training and rest 25% used for testing purpose. Total numbers of epochs are 60 and batch size is 16 in first round of training and testing. As we know that to improve the performance and

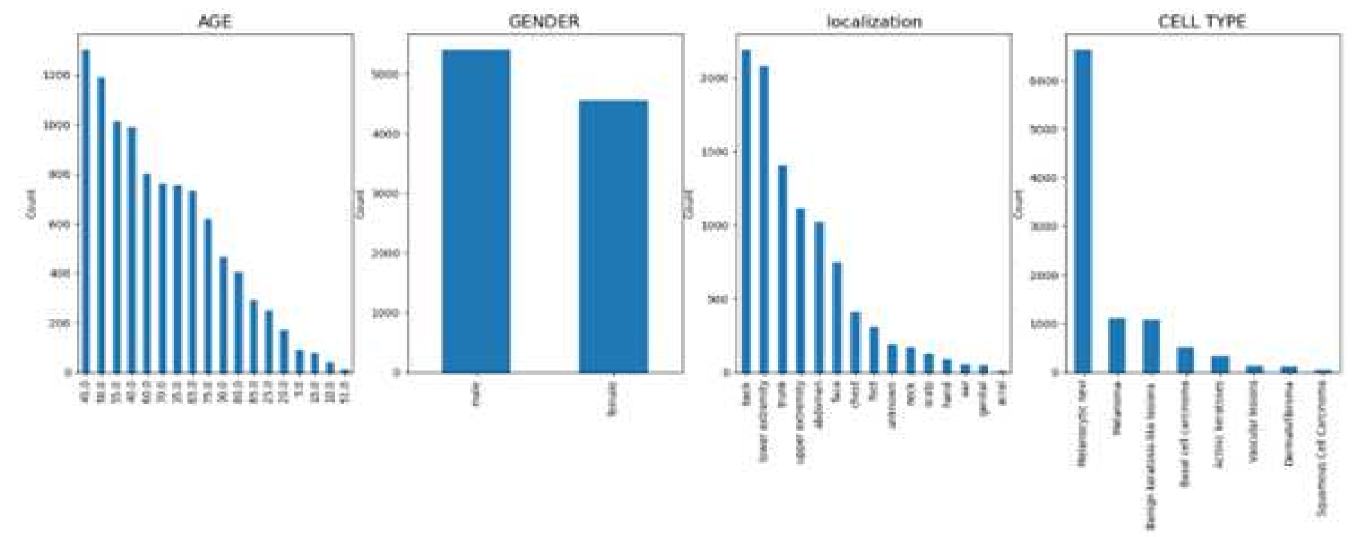

Fig. 5. - Exploratory data analysis.

multimodality, we used 100 SCC image as a new data set. Out of all images approximately 2500 image used as test set, rest for training. Data set images are randomly sampled from HAM_1000 new data set. Mostly all attributes' values were set to them by default ranges. One important parameter was learning rate which was exception always. Learning rate is based on probability that is very important hyper parameter to change or fluctuate according to time constraint. If it's fine-tuning to a network, our learning rate should must be decreased in same level[15]. Therefore, it was modified from default of 0.01 to 0. 001.We split each class data set (images) in test and training ratio that was almost 25 % and 75 % for both balance and imbalance data set.

accuracy of a model we perform iteration[17]. During each epoch, the model goes through the entire training dataset, updating its weights based on the computed gradients. Repeating this process for multiple epochs allows the model to learn from the data and improve its performance. In our research, we evaluated the performance of our classification model on a dataset using standard metrics to assess its effectiveness. The achieved accuracy of 92% indicates the overall correctness of our model in predicting instances correctly. Precision, measuring the accuracy of positive predictions, yielded a value of 86.66%, signifying the reliability of the model in identifying positive instances. Furthermore, the model demonstrated a high recall of 95.16%, emphasizing its ability to capture most actual

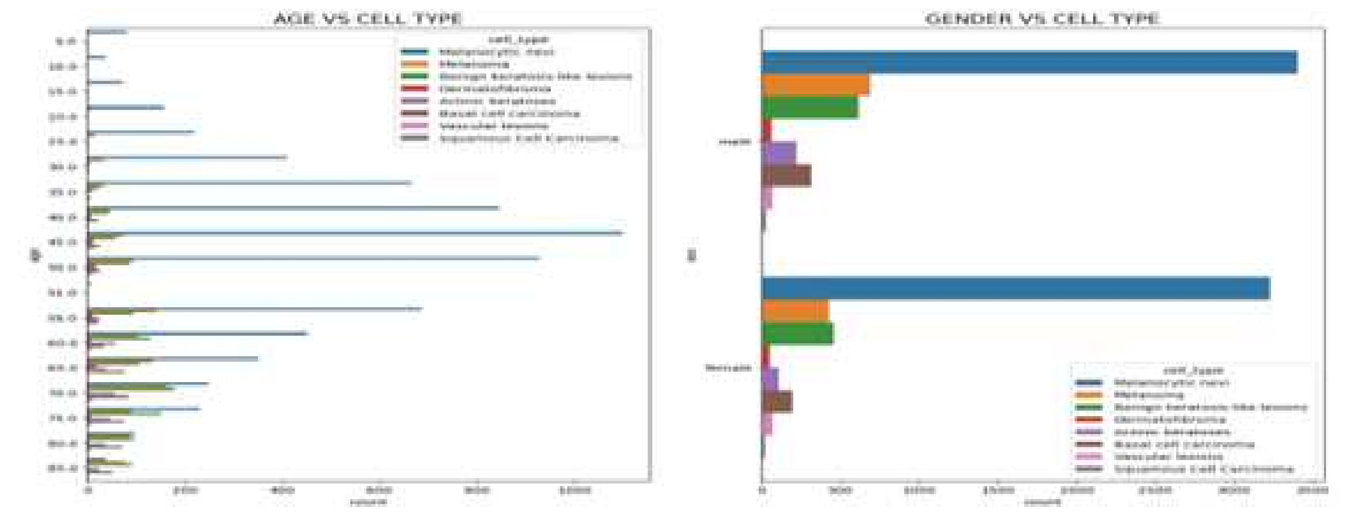

Fig. 6: Class distribution for data augmentation

For both ANN, CNN model images were resized and transformed. HAM10000 data set has 10015 skin cancer images of imbalance classes with total 10015 images of skin , including seven classes & attributes of skin lesions[3][16]. In extension of our data set that contain HAM_10000 + 100

positive instances. Model was capable of correctly identify negative instance with accuracy 49.90%. Additionally, the F1 Score, a harmonic mean of precision and recall, reached 90.71%, highlighting a favorable balance between precision and recall. These metrics collectively illustrate the robustness of our classification model, showcasing its competency in making accurate predictions across various aspects, and emphasizing its potential utility in practical applications[18], [19].

The confusion matrix for the model is shown in the Figure. 7. The confusion matrix is a fundamental tool used to evaluate the performance of classification models. It provides a comprehensive breakdown of the model's predictions, including True Positives (TP), True Negatives (TN), False Positives (FP), And False Negatives (FN).

The integrated confusion matrix adds valuable layer insight into the model's performance. The confusion matrix facilitates the calculation of sensitivity (recall) and specificity. Sensitivity measures the model's ability to correctly identify positive instances, such as potential cancerous conditions, while specificity gauges the accuracy in identifying negative instances, representing benign conditions. In the Figure.8 we represented about the results analysis of improper fraction of values in dataset. In the research paper on skin disease classification and cancer prediction, it is essential to address the presence of improper fractions or irregularities in the dataset values[4], [20], [21]. In the context of the dataset, improper fractions could represent instances where certain skin diseases or conditions are overrepresented, potentially influencing model training and evaluation[2].Therefore we analysis the results of skin type dataset as fraction classification incorrectly ,figure shows that our SCC images are properly classified up to 50% - 60 % that is best for initial phase of this type of skin cancer diagnosis.

The results of our proposed multi model system with deep learning shows batter accuracy on balance data as compared to unstructured/imbalance data of images. We extract those features that were performing well in the image's classification. However, this model is more flexible as compared to previous model. In generalization process we face various issues that were over fitting and under fitting of dataset. When we capture the data, it has noise and specific details that don't generalize to new data. Therefore, we can say that this is minor limitation of our proposed system.

VI. CONCLUSIONS

This field of medical science Skin disease classification with image and skin cancer prediction have become critical areas of research and development in the medical field. Skin diseases encompass a broad spectrum, ranging from benign conditions to potentially life-threatening cancers. Early and accurate diagnosis is essential for effective treatment planning and patient care. Our research on the integration of multimodal data for enhanced skin disease classification and cancer prediction has yielded promising and impactful results. The model, leveraging pre-trained multi-model Convolutional Neural Networks (CNNs) on the HAM_10000 Metadata and Squamous Cell Carcinoma (SCC) images, demonstrated exceptional performance across key metrics. The achieved accuracy of 92% signifies the model's high precision in correctly predicting instances, showcasing its reliability in clinical applications. The precision of 86.66% underscores the model and system accuracy in identifying positive value instances, while the recall rate of 95.16% emphasizes its effectiveness in capturing a significant proportion of actual positive cases. These metrics collectively affirm the model's robustness in skin disease classification, particularly in distinguishing between benign and potentially malignant conditions. However, it is essential to acknowledge the specificity value of 49.90%, indicating a room for improvement in correctly identifying negative instances. This aspect highlights an area for future optimization, ensuring a more balanced performance across both positive and negative predictions. The F1 Score of 90.71%, representing a harmonious balance between precision and recall, strengthens the model's potential for real-world clinical applications. Notably, the findings indicate that SCC images might hold a higher priority for skin cancer identification, as evidenced by the impressive accuracy rate of 92% on the original dataset. The integration of multimodal data sources, coupled with advanced machine learning techniques, opens avenues for revolutionizing dermatology and oncology. The proposed methodology has the potential to provide accurate, efficient, and early diagnoses for patients with skin diseases, thereby contributing significantly to improved patient care and treatment planning.

REFERENCES

[1] K. Cauvery, P. C. Siddalingaswamy, S. Pathan, and N. D'Souza, "A Multiclass Skin Lesion classification approach using Transfer learning based convolutional Neural Network," *Proc. 2021 IEEE 7th Int. Conf. Bio Signals, Images Instrumentation, ICBSII 2021*, 2021, doi: 10.1109/ICBSII51839.2021.9445175.

[2] M. Elbes, "Big Dermatological Data Service for Precise and Immediate Diagnosis by Utilizing Pre-trained Learning Models," pp. 0–24, 2023.

[3] T. M. Alam *et al.*, "An Efficient Deep Learning-Based Skin Cancer Classifier for an Imbalanced Dataset," *Diagnostics*, vol. 12, no. 9, 2022, doi: 10.3390/diagnostics12092115.

[4] R. A. Mehr and A. Ameri, "Skin Cancer Detection Based on Deep Learning," no. October, pp. 559–568, 2022, doi: 10.31661/jbpe.v0i0.2207-1517.Keywords.

[5] D. Sivabalaselvamani, K. Nanthini, D. Selvakarthi, V. M. Niranchan, L. S. Kumar, and P. Swetha, "Skin Melanoma Detection Using Image Augmentation," *Proc. 4th Int. Conf. Smart Electron. Commun. ICOSEC 2023*, pp. 1624–1630, 2023, doi: 10.1109/ICOSEC58147.2023.10275944.

[6] H. M. Rai and J. Yoo, "A comprehensive analysis of recent advancements in cancer detection using machine learning and deep learning models for improved diagnostics," *J. Cancer Res. Clin. Oncol.*, vol. 149, no. 15, pp. 14365–14408, Nov. 2023, doi: 10.1007/S00432-023-05216-W.

[7] T. G. Debelee, "Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review," *Diagnostics*, vol. 13, no. 19, Oct. 2023, doi: 10.3390/DIAGNOSTICS13193147.

[8] Y. Cheng, X. Zhao, R. Cai, Z. Li, K. Huang, and Y. Rui, "Semi-Supervised Multimodal Deep Learning for RGB-D Object Recognition Semi-Supervised Multimodal Deep Learning for RGB-D Object Recognition CRIPAC&NLPR, CASIA 2 Microsoft Research," 2016. [Online]. Available: https://www.researchgate.net/publication/301227188.

[9] J. Lipkova *et al.*, "Artificial intelligence for multimodal data integration in oncology," *Cancer Cell*, vol. 40, no. 10, pp. 1095–1110, Oct. 2022, doi: 10.1016/j.ccell.2022.09.012.

[10] A. Qoku, N. Katsaouni, N. Flinner, F. Buettner, and M. H. Schulz, "Multimodal analysis methods in predictive biomedicine," *Comput. Struct. Biotechnol. J.*, vol. 21, pp. 5829–5838, Jan. 2023, doi: 10.1016/j.csbj.2023.11.011.

[11] I. Moura, A. Teles, D. Viana, J. Marques, L. Coutinho, and F. Silva, "Digital Phenotyping of Mental Health using multimodal sensing of multiple situations of interest: A Systematic Literature Review," *J. Biomed. Inform.*, vol. 138, Feb. 2023, doi: 10.1016/j.jbi.2022.104278.

[12] C. Xin *et al.*, “An improved transformer network for skin cancer classification,” *Comput. Biol. Med.*, vol. 149, Oct. 2022, doi: 10.1016/j.compbiomed.2022.105939.

[13] L. Zhang, J. Zhang, W. Gao, F. Bai, N. Li, and N. Ghadimi, “A deep learning outline aimed at prompt skin cancer detection utilizing gated recurrent unit networks and improved orca predation algorithm,” *Biomed. Signal Process. Control*, vol. 90, p. 105858, Apr. 2024, doi: 10.1016/J.BSPC.2023.105858.

[14] H. Bhatt, V. Shah, K. Shah, R. Shah, and M. Shah, “State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review,” *Intell. Med.*, vol. 3, no. 3, pp. 180–190, Aug. 2023, doi: 10.1016/j.imed.2022.08.004.

[15] A. Kumar K, T. Y. Satheesha, B. B. L. Salvador, S. Mithileysh, and S. T. Ahmed, “Augmented Intelligence enabled Deep Neural Networking (AuDNN) framework for skin cancer classification and prediction using multi-dimensional datasets on industrial IoT standards,” *Microprocess. Microsyst.*, vol. 97, p. 104755, Mar. 2023, doi: 10.1016/J.MICPRO.2023.104755.

[16] Z. Jia, Y. Wang, S. Li, M. Yang, Z. Liu, and H. Zhang, “MICDnet: Multimodal information processing networks for Crohn’s disease diagnosis,” *Comput. Biol. Med.*, vol. 168, Jan. 2024, doi: 10.1016/j.compbiomed.2023.107790.

[17] E. Rezk, M. Haggag, M. Eltorki, and W. El-Dakhakhni, “A comprehensive review of artificial intelligence methods and applications in skin cancer diagnosis and treatment: Emerging trends and challenges,” *Healthc. Anal.*, vol. 4, Dec. 2023, doi: 10.1016/j.health.2023.100259.

[18] J. Jaworek-Korjakowska, M. H. Yap, D. Bhattacharjee, P. Kleczek, A. Brodzicki, and M. Gorgon, “Deep neural networks and advanced computer vision algorithms in the early diagnosis of skin diseases,” *State Art Neural Networks their Appl. Vol. 2*, pp. 47–81, Jan. 2022, doi: 10.1016/B978-0-12-819872-8.00010-0.

[19] M. Shahin, F. F. Chen, A. Hosseinzadeh, H. Khodadadi Koodiani, A. Shahin, and O. Ali Nafi, “A smartphone-based application for an early skin disease prognosis: Towards a lean healthcare system via computer-based vision,” *Adv. Eng. Informatics*, vol. 57, Aug. 2023, doi: 10.1016/j.aei.2023.102036.

[20] D. Chanda, M. S. H. Onim, H. Nyeem, T. B. Ovi, and S. S. Naba, “DCENSnet: A new deep convolutional ensemble network for skin cancer classification,” *Biomed. Signal Process. Control*, vol. 89, Mar. 2024, doi: 10.1016/j.bspc.2023.105757.

[21] K. Thurnhofer-Hemsi and E. Domínguez, “A Convolutional Neural Network Framework for Accurate Skin Cancer Detection,” *Neural Process. Lett.*, vol. 53, no. 5, pp. 3073–3093, Oct. 2021, doi: 10.1007/S11063-020-10364-Y.