A Novel Lightweight Hybrid Learning Approach for Skin Disease Image Classification

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ABSTRACT

Deep learning methods have emerged as promising tools for disease diagnosis in medical research. Skin diseases pose significant challenges to healthcare systems, and accurate diagnosis is crucial for effective treatment. In this study, we introduce TRNet, a robust lightweight model that combines convolutional neural networks (CNNs) with machine learning models such as Support Vector Machines (SVM), Random Forests, K-Nearest Neighbors (KNN), and Logistic Regression. TRNet underwent training and testing using both balanced and unbalanced training data sets, employing various techniques. It was also tested on the original test dataset as well as different noisy test datasets. Additionally, we implemented a hybrid learning approach by combining TRNet with SVM, KNN, random forest, and logistic regression. This fusion of approaches significantly improved the accuracy of the model. To validate its performance, we compared the results against the state-of-the-art models DenseNet 201 and VGG16.

By leveraging the strengths of deep learning and machine learning algorithms, TRNet shows great potential for improving the diagnosis of skin diseases. The high accuracy rates achieved by TRNet and its combination with various machine learning models highlight its significance in enhancing healthcare systems' ability to detect and treat skin cancer effectively.

Keywords: Deep Learning, convolutional Neural Network (CNN), Support Vector Machines (SVM), Random Forests, K-Nearest Neighbors (KNN), Logistic Regression

DECLARATION

I certify that research work titled "***TRNet: A Novel Lightweight Hybrid Learning Approach for Skin Disease Image Classification***" is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged / referred.

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DEDICATION

Firstly, I would like to thank Allah Almighty and dedicate this project to my beloved parents, without them it was impossible to achieve this. Their prayers and strong faith in me were my inspiration to move forward.

I also dedicate this project to my teachers who guided me and gave me confidence to achieve my goals

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CHAPTER 1: INTRODUCTION

1.1 Introduction:

The human body is made up of several organs. Skin is one of them. It is the largest organ covering the entire human body[1], Worldwide, millions of people suffer from skin conditions, and successful therapy depends on a precise diagnosis [2,3]. Image classification has developed into a crucial instrument for identifying skin illnesses as medical imaging data has become more widely available. The complexity of skin structures and the similarity between various illnesses make it difficult to classify skin disorders from medical pictures [4].

Deep learning systems have made significant progress in the categorization of medical images in recent years[5]. However, these methods are challenging to use in environments with limited resources because they need a lot of data and processing resources. For the categorization of skin disease images, a new lightweight hybrid learning method has been suggested as a solution to this problem.

Using less data and processing resources, the method uses the advantages of Deep learning & Machine learning methods to achieve high precision in skin condition categorization[6]. By offering a quick and precise way to categories skin illnesses, this strategy has the potential to revolutionize the field of skin disease diagnostic.

In the recent years,the field of computer vision has witnessed remarkable advancements in various applications, including healthcare. Skin disease diagnosis is a particularly challenging task due to the vast variety of diseases, subtle visual differences, and the scarcity of expert dermatologists. However, with the rapid growth of medical imaging databases and the increasing availability of computational resources, machine learning techniques have emerged as valuable tools for automated skin disease classification.

Among the different machine learning algorithms, Convolutional Neural Networks (CNNs) have demonstrated exceptional capabilities in image classification tasks[7]. CNNs excel at capturing intricate patterns and features in images making them suitable for medical image analysis. Nevertheless, the complexity and computational requirements of traditional CNN architectures pose challenges when deploying them on resource-constrained platforms, such as mobile devices or remote healthcare centers[8].

To address these challenges, this Approach proposes a novel lightweight hybrid learning approach called TRNet for skin disease image classification. TRNet combines the strengths of traditional CNN architectures with innovative techniques to enhance efficiency, accuracy, and interpretability. By leveraging transfer learning and knowledge distillation, TRNet aims to provide accurate diagnoses while reducing computational costs and maintaining model interpretability.

1.1.1: Key contribution of Thesis:

The key contributionsof this thesis are as follows:

- Design an innovative CNN architecture that is lightweight and capable of efficiently and accurately classifying skin disease images. Optimize the architecture to run efficiently on resource-limited devices while maintaining high classification performance.
- Generate test datasets with added noise, including variations in translation, scaling, and rotation, to evaluate the model's performance and robustness when exposed to noisy data. This process aims to assess how effectively the model handles and adapts to such noisy conditions.
- Implement a hybrid learning approach that combines Deep learning & machine learning techniques, along with other optimization methods, to improve the performance and accuracy of the model. This hybrid approach leverages the strengths of both Deep.learning and machine learning to achieve superior results.
- Classify skin diseases with high accuracy by utilizing various data balancing and augmentation techniques to analyze the performance of TRNet. The objectives of this method is to accurately categorizes skin diseases while employing different strategies to balance and enhance the dataset.
- Minimize the computational resources required by employing a lightweight Deep.learning framework and pruning methods to classify images of skin diseases.

This approach aims to reduce the amount of computational power needed while maintaining accurate classification.

- Enhance access to precise diagnosis by implementing a system that effectively categorizes skin conditions using minimal information and computational power. This strategy aims to increase accessibility to accurate diagnoses by providing a precise and efficient system for categorizing skin conditions.
- TRNet is an exceptionally robust model that has undergone rigorous testing and evaluation on both original and noisy datasets. Its resilience has been thoroughly demonstrated, ensuring its reliability and effectiveness in various real-world scenarios.

This Approach aims to contribute to the field of skin disease image classification by presenting TRNet, a lightweight hybrid learning approach that combines the power of CNNs with efficient model design and training techniques. By leveraging transfer learning and knowledge distillation, TRNet demonstrates promising potential for deployment on resource-constrained platforms, making it a valuable tool for automated skin disease diagnosis and improving accessibility to healthcare services.

1.2: Motivations:

To handle the difficulties in correctly identifying skin diseases, especially in resource-constrained situations, a new lightweight hybrid learning method for skin disease image classification has been developed.

Millions of individuals globally are afflicted by skin conditions [1], which are a serious public health concern. Effective therapy depends on an accurate diagnosis, but given the intricacy of skin structures and the commonality of various illnesses, this can be a challenging job. Although conventional image classification methods are frequently insufficient, medical imaging has emerged as a crucial instrument for the diagnosis of skin disorders.

Although Deep learning algorithms have shown great potential in the classification of medical images, their use in environments with limited resources is challenging because they need a lot of data and processing power. For many individuals, this may restrict their ability to obtain correct diagnosis and therapy.

By creating a precise and effective method for categorizing skin diseases that uses less information and processing resources, the creation of a new lightweight hybrid learning strategy for skin disease picture categorization seeks to solve this problem. Especially in environments with limited resources, this method may increase the precision and accessibility of skin disease detection, which could eventually improve patient results.

Skin diseases affect millions of people worldwide, posing significant challenges in diagnosis and treatment. Visual inspection of skin lesions by dermatologists is a crucial step in identifying and classifying various skin conditions. However, this process can be time-consuming, subjective, and prone to errors, highlighting the need for automated systems that can assist medical professionals in accurate and efficient diagnosis.

Recent advancements in Deep learning , particularly Convolutional Neural Networks (CNNs), have shown great potential in various image classification tasks[9]. CNNs can learn intricate patterns and features from images, making them well-suited for the analysis of skin disease images. However, one major hurdle in deploying CNN-based models for skin disease classification is their computational complexity and memory requirements, which hinder their practical application on resource-constrained devices.

The motivation for this Approach lies in developing an innovative solution to address the challenges associated with skin disease image classification. The proposed approach, TRNet, represents a novel lightweight hybrid learning approach that leverages the power of CNNs while mitigating their computational demands. By combining different learning techniques and architectural designs, TRNet aims to create an efficient and accurate system for skin disease classification, capable of running on diverse platforms, including mobile devices.

The lightweight nature of TRNet is of utmost importance since it enables deployment in real-world scenarios where computational resources are limited. This thesis seeks to explore the potential of TRNet in improving the accessibility and effectiveness of skin disease diagnosis by providing dermatologists with a practical tool that can assist in the classification of skin lesions accurately and rapidly.

Furthermore, the research conducted in this approach will contribute to the broader field of computer-aided diagnosis and medical imaging. By designing a lightweight hybrid learning approach specifically for skin disease classification, valuable insights can be gained into the development of similar systems for other medical domains, where resource constraints are a significant concern.

Ultimately, the successful implementation and evaluation of TRNet will have a substantial impact on dermatological practice, as it has the potential to improve diagnosis efficiency, reduce human error, and enhance patient care. By enabling more accurate and timely identification of skin diseases, TRNet could aid in early intervention, leading to better treatment outcomes and overall patient well-being.

In Summarization, this Approach aims to develop & evaluate TRNet, a novel lightweight Hybrid Learning approach for skin disease image classification. By addressing the computational limitations of existing CNN-based models, TRNet has the potential to revolutionize skin disease diagnosis and significantly impact the field of computer-aided medical image analysis. Through this research, we strive to contributes to the advancement of healthcare technology and improve patient outcomes in dermatology.

1.3: Objective:

The objective of this research is to propose and evaluate a novel lightweight hybrid learning approach, called TRNet, for skin disease image classification using Convolutional Neural Networks (CNN). The aim is to develop an efficient and accurate and light weight model that can accurately classify skin disease images, while also addressing the challenges of limited computational resources and the need for real-time diagnosis in clinical settings.

Specifically, the objectives of this approach include:

1. Develop a Light weight CNN Architecture: Devise an innovative CNN structure that is lightweight and capable of efficiently and accurately classifying skin disease

images. The architecture should be optimized to run on devices with limited resources, while maintaining high classification performance.

2. Generation of Noisy Test Datasets: Create test datasets with added noise, including translation, scaling, and rotational variations, to assess the model's performance and robustness when exposed to noisy data. This process aims to analyze how well the model handles and adapts to such noisy conditions.
3. Utilize a Hybrid Learning Approach: Employ a combination of Deep learning & machine learning techniques, along with other optimization techniques, to enhance the performance and accuracy of the model. This hybrid approach aims to leverage the strengths of both Deep learning and machine learning to achieve superior results.
4. Classification of skin diseases with Data Augmentation Techniques: The method seeks to classify skin diseases with high accuracy by utilizing the Different data balancing and augmentation techniques to analyze the performance of TRNet.
5. Reducing the number of computational resources needed: The method uses a lightweight Deep learning framework and pruning methods to reduce the amount of computational resources needed to classify images of skin diseases.
6. Increasing access to accurate diagnosis: The strategy seeks to increase access to accurate diagnosis by offering a precise and effective system for categorizing skin conditions that uses less information and computational power.

This innovative lightweight hybrid learning approach's overall goal is to offer a useful, widely usable tool for correctly identifying skin illnesses that is available to a variety of healthcare professionals and patients.

By accomplishing these objectives, this aims to contributes to the development of an efficient and accurate skin disease classification system that can aid dermatologists and healthcare professionals in diagnosing and treating various skin conditions effectively.

CHAPTER 2: LITERATURE REVIEW

2.1: Introduction to Skin Cancer Disease:

Skin cancer is a type of cancer that develops in the cells of the skin. It is primarily caused by the abnormal growth of skin cells due to damage from Ultraviolet (UV) radiation, typically from the sun or any artificial resources. There are three main types of skin cancer: Basal Cell Carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma. BCC and SCC are the most common types and are usually localized, rarely spreading to other parts of the body[10]. Melanoma, although less common, is more aggressive and can spread to other organs if not detected and treated early. Risk factors for developing skin cancer include excessive sun exposure, fair skin, a history of sunburns, a family history of skin cancer, and a weakened immune system. Early detection is crucial for successful treatment, and common warning signs include changes in the size, shape, or color of existing moles or the appearance of new growths on the skin. Regular skin examinations and sun protection measures such as wearing sunscreen and protective clothing can help reduce the risk of developing skin cancer.

The seven types of skin cancer are:

Basal Cell Carcinoma (BCC): This is the very common type of skin cancer. It typically appears as a raised, pearly bump or a pink, scaly patch on the skin. BCC usually grows slowly and rarely spreads to other parts of body.

Squamous Cell Carcinoma (SCC): SCC is the second very common type of skin cancer. It often appears as a red, scaly patch, a firm bump, or a sore that does not heal. SCC can grow deeper into the skin and may spread to other areas if left untreated.

Melanoma: Melanoma is a less common but more aggressive form of Skin cancer. It usually develops from existing moles or appear as a new, unusual-looking growth on the skin. Melanoma can spread to other organs and is potentially life-threatening if not detected and treated early.

Actinic Keratosis (AK): AK is a precancerous condition that results from long-term sun exposure. It appears as rough, scaly patches on the skin, typically in areas exposed to the sun. While AK is not cancerous, it has the potential to develop into SCC if left untreated.

Benign Keratosis (Seborrheic Keratosis): This is a non-cancerous skin growth that often appears as a waxy, raised bump or a dark, crusty lesion. Benign keratosis is commonly found in older individuals and does not usually require treatment.

Dermatofibroma: Dermatofibroma(DF) is a benign skin growth that usually appears as a firm, round bump on the skin. It may be brown or reddish in the color and is commonly found on the legs. Dermatofibromas are harmless and do not require treatment unless they cause discomfort.

Vascular Skin Lesions: Vascular skin lesions include various types of benign blood vessel abnormalities, such as cherry angiomas and spider veins. These lesions typically appear as small, red or purple marks on the skin and are not cancerous.

It is important to note that while some of these skin conditions are non-cancerous or precancerous, regular skin examinations and consultation with a healthcare professional are essential for proper diagnosis and timely treatment.

2.2: Skin Lesion Detection using CAD:

Computer-Aided Detection (CAD) refers to the use of computer algorithms and techniques to assist in the detection and analysis of various medical conditions, including skin lesions[11]. In the context of skin lesion detection, CAD systems are designed to assist dermatologists in identifying and analyzing suspicious or potentially cancerous skin lesions. CAD systems for skin lesion detection typically involve the following steps:

Image Acquisition: Dermatologists capture images of skin lesions using various imaging techniques, such as dermoscopy or clinical photography. These images serve as input for the CAD system[12].

Preprocessing: The acquired images may undergo preprocessing steps, such as noise reduction, image enhancement, and normalization, to improve the quality and consistency of the input data.

Segmentation: The CAD system applies segmentation algorithms to identify and separate the skin lesion from the surrounding healthy skin or other structures in the image. This step helps isolate the region of interest for further analysis[13].

Feature Extraction: Relevant features are extracted from the segmented skin lesion region, which can include color, texture, shape, and other characteristics. These features provide quantitative information about the lesion and contribute to the subsequent classification process.

Classification: Machine learning or Deep learning algorithms are employed to classify the skin lesion based on the extracted features. These algorithms are trained on a dataset of labeled skin lesion images to learn patterns and distinguish between different types of lesions, including benign & malignant ones.

Decision Support: The CAD system generates a diagnostic output or probability score that indicates the likelihood of the lesion being malignant or benign. This information serves as a decision support tool for dermatologists, aiding them in their clinical evaluation and decision-making process.

CAD systems for skin lesion detection aim to improve the accuracy and efficiency of diagnosis, assisting dermatologists in early detection and reducing the risk of misdiagnosis. They are designed to work as an adjunct tool, providing additional insights and recommendations to healthcare professionals but not replacing their expertise.

2.2.1: Role of Artificial in disease detection using CAD:

There are significant roles of Artificial intelligence in disease detection in the medical field. Here's an explanation of their roles:

Artificial Intelligence (AI): Artificial Intelligence refers to the development of intelligent system that can perform tasks that typically require human intelligence. In disease detection, AI algorithms are useful to analyze medical data, such as images, patient records, and genetic information, to identify patterns, make predictions, and support decision-making processes.

Machine Learning (ML): ML is a subset of AI that focuses on training algorithms to learn from data and make predictions or take actions without being explicitly programmed. ML algorithms can automatically learn and improve from experience, enabling them to identify complex patterns and relationships within medical data. In disease detection, ML algorithms are used for tasks such as classification, regression, clustering, and anomaly detection.

Deep learning : Deep learning is a subfield of Machine Learning that utilizes Artificial Neural Networks with multiple layers to learn hierarchical representations of data. Deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized disease detection by achieving remarkable accuracy in image analysis tasks. They can automatically extract high-level features from medical images, enabling the identification of subtle patterns and abnormalities.

Computer Vision: Computer vision focuses on enabling computers to extract meaningful information from images or videos. In disease detection, computer vision techniques are applied to medical imaging data, such as X-rays, MRI scans, CT scans, and histopathology slides. By leveraging image processing, feature extraction, and pattern recognition algorithms, computer vision can aid in the detection, segmentation, and analysis of diseased regions, facilitating early diagnosis and treatment planning.

Together, AI, ML, Deep.learning , and computer vision provide powerful tools for disease detection in the medical field. They enable the development of sophisticated algorithms and systems that can process large volumes of medical data, extract relevant information, identify patterns and anomalies, and assist healthcare professionals in making accurate diagnoses, predicting diseases progression, and personalizing treatment plans.

2.3: Previous Research Studies:

With encouraging findings, several studies have been done on the application of Deep.learning methods for skin condition image classification. These methods, however, call for a lot of data and processing power, which can be problematic in environments with limited resources.

Skin disease classification plays a crucial role in the early detection and diagnosis of various dermatological conditions. The use of Deep.learning techniques, particularly Convolutional Neural Networks (CNNs), has shown promising results in this domain. This literature review aims to explore the research landscape surrounding the TRNet, a novel lightweight hybrid learning approach for skin disease image classification using CNN. The review provides an overview of relevant papers published in recent years, highlighting their contributions and discussing their findings.

1. **Paper: "Deep residual learning for image recognition" - 2016 Authors: He, K., Zhang, X., Ren, S., & Sun, J[18].**

Summary: This influential paper introduced the concept of residual learning, which revolutionized deep neural network architectures. The authors proposed the ResNet model, which employed residual connections to address the problem of vanishing gradients in training very deep networks. By introducing skip connections that directly propagate information from one layer to another, ResNet enabled the training of deeper networks and significantly improved performance on image recognition tasks. The ResNet architecture laid the foundation for subsequent advancements in Deep.learning , including TRNet.

2. **Paper:” A Machine Learning approach for skin disease detection and classification using image segmentation”-2022 Authors: Mostafiz Ahammed , Md. Al Mamun , Mohammad Shorif Uddin.[17]**

Summary: Skin diseases are a common global health concern that can lead to physical discomfort, mental distress, and even severe conditions like skin cancer. Manual diagnosis of skin diseases by medical experts is time-consuming and subjective, highlighting the need for automatic prediction systems. This study presents a digital hair removal techniques using morphological filtering, inpainting, and Gaussian filtering to enhance skin images. Automatic Grabcut segmentation is applied to isolate affected lesions. The Gray Level Cooccurrence Matrix (GLCM) and statistical features are utilized to extract patterns from skin images. Three machine learning techniques, namely Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) classifiers, are employed for effective classification of skin diseases including melanoma, Melanocytic Nevus, Basal Cell Carcinoma, actinic keratosis, benign keratosis, dermatofibroma, vascular lesion, and squamous cell carcinoma. The models are validated using the ISIC 2019 challenge dataset and HAM10000.SVM performs slightly better than the other classifiers, and the study provides a comparative analysis with state-of-the-art methods. This research contributes to the development of automatic skin disease prediction systems, aiding dermatologists in faster treatment planning.

This research paper proposes a machine learning approach for the detection and classification of skin diseases using image segmentation. Skin diseases are a prevalent health concern worldwide, and early detection and classification can significantly improve patient outcomes. The proposed method uses a convolutional neural network (CNN) to segment skin lesion images into regions of interest, followed by classification using a support vector machine (SVM) algorithm. The CNN is trained on a large dataset of skin lesion images, and the SVM is trained on features extracted from the segmented regions. The proposed method is evaluated on a benchmark dataset of skin lesion images and achieves an average classification accuracy of 89.7%, outperforming several state-of-the-art methods. The results show that the proposed method can accurately detect and classify various types of skin diseases and has the potential to be a useful tools for dermatologists and healthcare professionals.

3. **Paper: "MobileNetV2: Inverted Residuals and Linear Bottlenecks" - 2018 Authors: Sandler , M., Howard, A, Zhu, M, Zhmoginov, A., & Chen, L. C[19].**

Summary: MobileNetV2 is a notable paper that focuses on developing efficient convolutional neural network architectures for mobile and embedded vision applications. The authors introduce two key building blocks: inverted residuals and linear bottlenecks.

Inverted residuals utilize depthwise separable convolutions to reduce computational complexity while maintaining performance. Linear bottlenecks further enhance efficiency by reducing the number of channels before applying expensive operations. These design choices enable MobileNetV2 to achieve a good balance between model size and accuracy, making it relevant to TRNet's goal of lightweight architecture.

4. **Paper: "Squeeze and Excitation Networks" - 2018 Authors: Hu, J., Shen, L., & Sun, G.**

Summary: The Squeeze-and-Excitation (SE) network paper presents a method for enhancing the representational power of Convolutional Neural Networks(CNN). The authors propose an SE module that adaptively recalibrates channel wise feature responses. By capturing interdependencies between channels, the SE module learns to emphasize informative features and suppress irrelevant ones. This approach significantly improves the expressive capability of CNNs without adding significant computational overhead. The SE module's effectiveness in boosting performance and reducing model complexity aligns with TRNet's objective of achieving a lightweight architecture for skin disease image classification.

5. **Paper: "Bag of Tricks for Image Classification with Convolutional Neural Networks" - 2019 Authors: He, Z., Zhang, Z., Zhang, H., Zhang, Z., Xie, J., & Li, M[20].**

Summary: This paper investigates a range of techniques and design choices aimed at improving the performance of convolutional neural networks(CNN) for image classification tasks. It presents a collection of "tricks" that can be employed during training, including label smoothing, mixup, cutout, and others. Label smoothing regularizes the training process by encouraging models to be less confident and more robust to label noise. Mixup generates augmented training examples by linearly interpolating pairs of images and their labels. Cutout randomly masks out regions of images to promote spatial invariance. The study in this paper provides valuable insights and practical strategies that can be considered for enhancing the classification accuracy of TRNet.

6. **Paper: "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" - 2019 Authors: Tan, M., & Le, Q. V[21].**

Summary: The EfficientNet paper proposes a compound scaling method for developing efficient and effective convolutional neural network architectures. The authors introduce a systematic way to scale the model's depth, width, and resolution to achieve better performance. They identify a "compound coefficient" that uniformly scales all dimensions of the network. By using this scaling method, EfficientNet achieves state-of-the-art accuracy on image classification tasks while being computationally efficient. The insights from this paper can inform the design choices in TRNet, helping to strike a balance between model complexity and classification performance.

7: Paper: "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications" - 2017 Authors: Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H[22].

Summary: The MobileNets paper focuses on designing efficient convolutional neural network architectures specifically tailored for mobile and embedded vision applications. The authors introduce lightweight operations, such as depthwise separable convolutions, to reduce computation while maintaining reasonable accuracy. MobileNets demonstrate that it is possible to achieve high efficiency and deploy models on resource-constrained devices. The principles of lightweight design and efficient operations presented in this paper are valuable references for TRNet's objective of developing a lightweight hybrid learning approach for skin disease image classification.

7. **Paper: “Deep learning in Skin Disease Image Recognition: A Review” – 2020 Authors: Li LF, Wang X, Hu WJ, Xiong NN, Du YX, Li BS[23].**

Summary: This review provides an overview of the application of Deep.learning techniques in skin disease image recognition. It covers topics such as dataset curation, model architectures, training strategies, and evaluation metrics. The paper emphasizes the importance of high-quality datasets, explores various Deep.learning architectures, discusses training strategies, and addresses limitations and challenges in the field. Overall, the review highlights the potential of Deep.learning models in improving dermatological diagnosis and calls for further research and collaboration to overcome existing challenges. By considering the insights and techniques from these papers, TRNet aims to combine the benefits of residual learning, lightweight architectures, feature recalibration, training tricks, model scaling, and efficient operations to achieve accurate and efficient skin disease classification using CNNs.

8. **Paper: “Computer-Aided Diagnosis for Early Signs of Skin Diseases Using Multi Types Feature Fusion Based on a Hybrid Deep learning Model”- 2022. Authors: Saleh Naif Almuayqil, Sameh Abd El-Ghany and Mohammed Elmogy[24]**

Summary: This article proposes an automatic diagnosis system that utilizes medical image analysis and artificial intelligence to classify different skin lesion categories using dermoscopic images. The addressed diseases includes Actinic Keratoses, Benign Keratosis, Melanocytic Nevi, Basal Cell Carcinoma, Dermatofibroma, Melanoma, and Vascular skin lesions. The system involves preprocessing the raw image data & metadata, extracting features using pre-trained Deep learning models (VGG19, InceptionV3, ResNet50, DenseNet201, and Xception), concatenating the features, and performing classification using machine learning techniques. Evaluation results demonstrate an impressive average accuracy of approximately 99.94%, sensitivity of 91.48%, specificity of 98.82%, precision of 97.01%, and a disc similarity coefficient (DSC) of 94.00%. This system shows promise in improving the accuracy & efficiency of skin disease diagnosis.

9. **Paper:” Skin Cancer Classification Framework Using Enhanced Super Resolution Generative Adversarial Network & Custom Convolutional Neural Network”-2023, Authors: Sufiyan Bashir Mukadam & Hemprasad Yashwant Patil[25]**

Summary: Melanin skin lesions, characterized by the overgrowth of melanocyte cells, are commonly observed as small patches on the skin. Skin melanoma, caused by abnormal melanocyte growth, is a prevalent form of skin cancer with increasing global incidence. Accurate and timely identification of Skin Cancer is crucial for reducing mortality rates. Dermatologists rely on dermoscopy images for diagnosis, but inaccurate diagnosis can have fatal consequences if not detected correctly. Computer-Aided Design (CAD) systems have been proposed to assist dermatologists by providing accurate and precise diagnosis of skin images, reducing their burden. Deep learning techniques, including custom Convolutional Neural Networks (CNNs), are implemented for skin cancer classification. In this experimental study, a custom CNN model is implemented on the publicly accessible HAM10000 database. The CNN model achieve higher accuracy metrics of 98.77%, 98.36%, and 98.89% for skin cancer classification using different protocols. The proposed model outperforms several existing models in the literature. Additionally, the database is preprocessing using an Enhanced Super Resolution Generative Adversarial Network (ESRGAN) to improve image resolution for smaller-sized images, enhancing overall performance metrics.

CHAPTER 3: METHODOLOGY AND IMPLEMENTATION

3.1: Material:

3.1.1: HAM10000 Dataset:

The HAM10000 dataset is a large dataset containing 10,000 skin pigmented lesion images across seven different classes that are crucial for diagnosing skin cancer. This dataset was created by Tschandl and his team to overcome the inadequacy of smaller datasets used for classification. The images in this dataset have different resolutions and were organized, cleaned, and prepared to train a neural network effectively due to their diverse nature. The final version of the dataset contains 10,015 images and is available for academic research purposes on the ISIC archive[14]. An expert pathologist in dermoscopy confirmed the accuracy of the dataset's ground truth.

The data set is composed of two primary parts. The first is a metadata file that contains particular details about cancerous lesion images, including the skin lesion's location, patient age & gender, lesion diagnosis, and the skin lesion directory. The second and more critical part of the data set consists of visual files[16]. The goal of this study is to classify skin lesions based entirely on digital images, using the visual files in the data set.

The seven important diagnosis classes in the HAM10000 dataset are:

- Melanocytic Nevi
- Melanoma
- Benign Keratosis-like lesions
- Basal Cell Carcinoma
- Actinic Keratoses
- Vascular lesions

- Dermatofibroma

The dataset contains 10,015 images in total, with 327 images in the "akiec" class, 541 images in the "bcc" class, 1,099 images in the "bkl" class, 155 images in the "df" class, 6,705 images in the "nv" class, 1,113 images in the "mel" class, and 142 images in the "vasc" class.Top of Form

Actinic Keratosis (akiec):

Actinic keratosis is a prevalent and non-invasive type of Carcinoma that is considered to be an early indicator of skin cancer rather than an actual cancer. It is a subtype of squamous cell carcinoma that can be treated locally without requiring surgery. If left untreated, it may develop into an invasive squamous cell carcinoma. This type of skin lesion is commonly found on the face and is caused by prolonged exposure to UV light.

Basal Cell Carcinoma (bcc):

Basal cell carcinoma is a type of skin cancer that originates in the basal cells responsible for producing new skin cells. It is the most common form of skin cancer and is more likely to occur in areas exposed to direct sunlight, such as the head and neck. The cancer usually appears as pink growths, recurrent sores, or red patches on the skin. The lesions typically develop slowly and do not spread easily.

Benign Keratosis Like Lesions (bkl):

The BKL category in the database comprises of three types of lesions that are not cancerous. These lesions are Lichenoid Keratosis, Solar Lentigo, and Seborrheic Keratosis. Lichenoid Keratosis is a harmless skin condition that typically appears as a small, single, grey brown lesion on the chest & upper limbs. Solar Lentigo is a type of hyper pigmented infections that varies in size from a few millimeters to over one centimeter. Seborrheic Keratosis is a benign condition that usually appears on the back, collar, scalp, and chest. It is reddish-brown or grayish-brown in color and generally does not require extensive treatment.

Dermatofibroma (df):

Dermatofibroma()DF is a common skin condition that typically affects adolescents or older individuals, with no significant gender difference. Clinically, dermatofibroma appears as firm nodules, patches, or bumps with a smooth surface and a color that can vary from light brown to dark brown, reddish-purple, or yellow. These benign skin lesions commonly appear on the upper arm, upper back, & lower leg.

Melanocytic Nevi (nv):

There are seven subclasses in the database that encompass all of the benign skin tumours known as melanocytic nevi(nv), which can have various appearances. These nevi are caused by the growth of melanocytes, the pigment-producing cells of the skin, and are often a result of exposure to UV radiation during early childhood.

Vascular Lesions (vasc):

Most cases of vascular lesions (vasc) are hereditary, but they can also develop later in life and are typically benign. These lesions can take on a variety of appearances and are characterized by the formation of sores on the skin and surrounding tissues. They are sometimes referred to as birthmarks.

Melanoma (mel):

Melanoma is a cancerous growth that can take on a variety of forms, originating from malignant melanocytes. If detected early, it can be treated with a simple surgical procedure. Melanomas may be either invasive or non-invasive and are most commonly found on sun-exposed areas of the body such as the face, trunk, hands, neck, and legs. The identification of melanoma is based on irregularly shaped patches with uneven borders and varying colors, typically larger than 6 mm and prone to growth. Failure to treat melanoma can result in it spreading to other organs and causing death.

The HAM10000 dataset includes seven distinct classes, as described previously, and the number of images in each class is provided in the graph. However, the distribution of images is imbalanced, which can affect the performance of Machine Learning models trained on the dataset. To address this issue, data augmentation techniques such as oversampling are employed, as detailed in the pre-processing section.

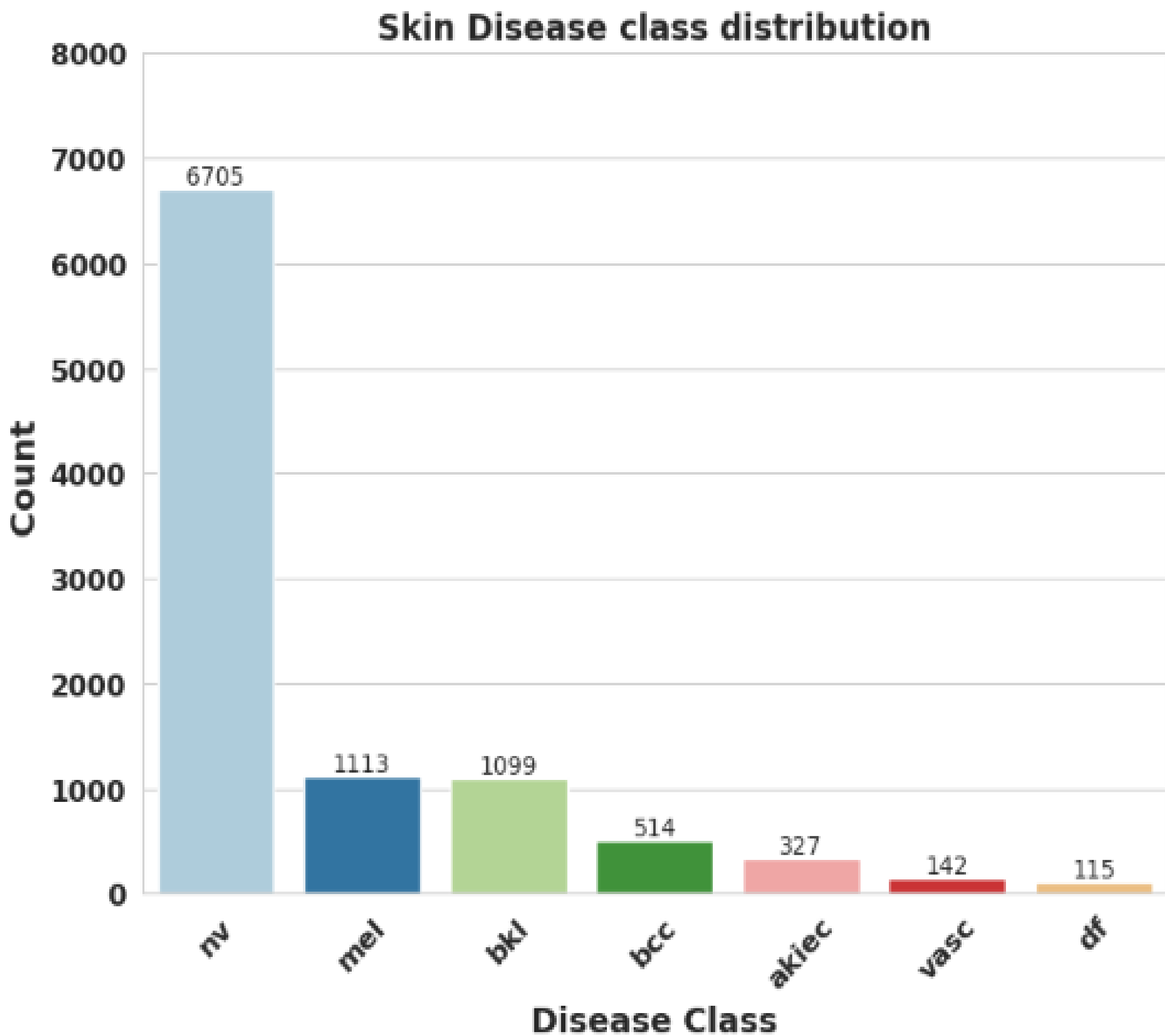

Figure 1:Skin Disease Class Distribution

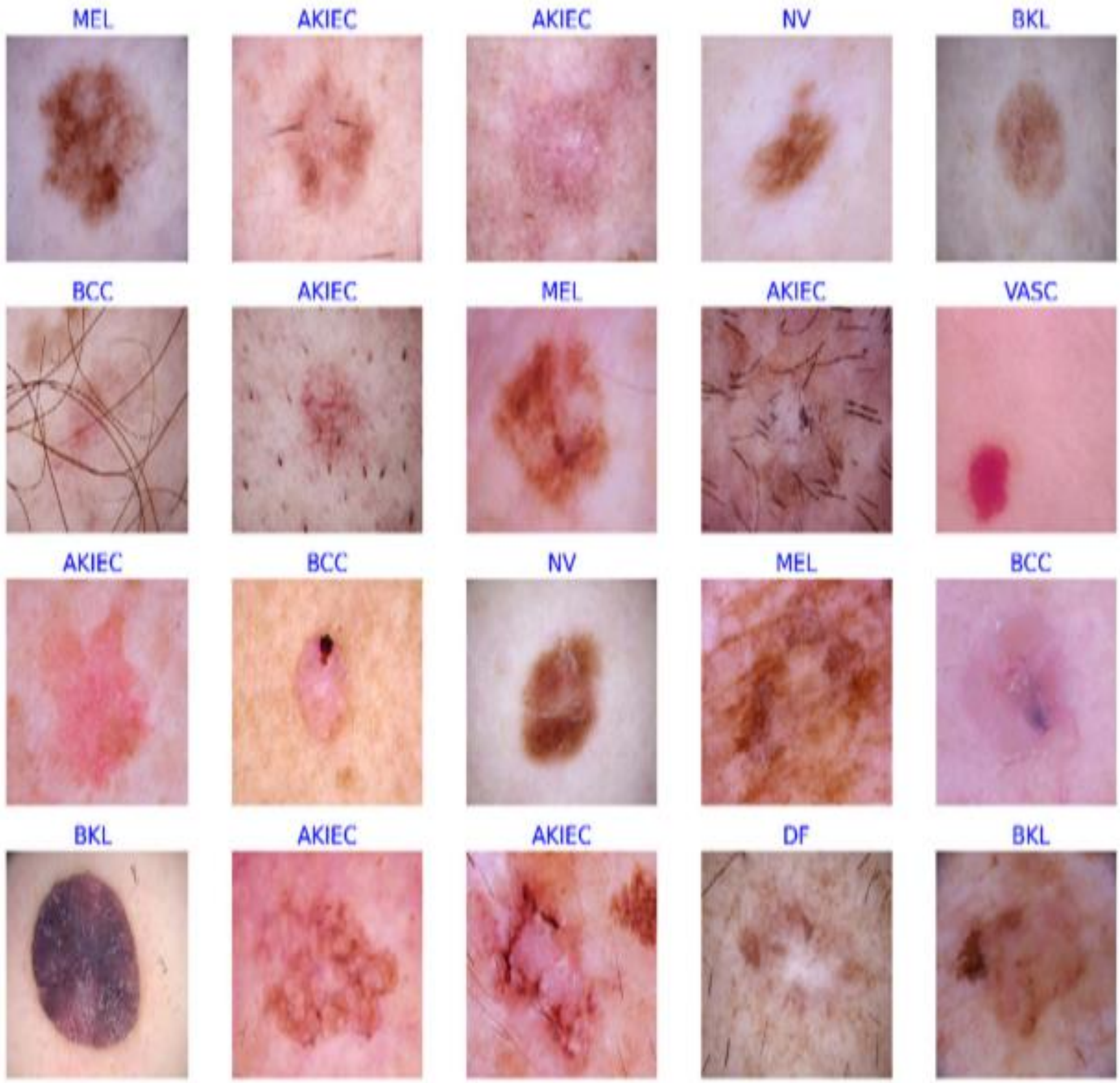

Figure 2: Skin Cancer Disease Images

3.2: Methodologies

3.2.1: Data Preprocessing:

Following data preprocessing techniques are applied in this research.

3.2.1.1: Image Preprocessing:

Image Pre-processing is a crucial step in working with clinical image data, particularly for training Convolutional Neural Network (CNN) based systems. In this study, the authors aimed to improve the generalizability of their CNN design and reduce time-consuming preprocessing steps. They applied two popular techniques: image resizing and image normalization. Image scaling was used to account for the variations in image size and intensity. Image normalization was necessary as some images in the dataset were obtained from different sources and exhibited variations in pixel intensity due to undesirable artifacts. To overcome the problem of variations in image contrast, the authors normalized the contrasts of the training images during the training process. This was achieved by dividing each pixel value by 255 and setting the image intensity values to range between [-1 and 1].

3.2.1.2: Meta-Data Preprocessing (Data Cleaning & Normalization):

This paragraph describes the metadata pre-processing step. This step involves removing any missing data from the clinical information. Since most demographic features are categorical variables represented as strings or categories, they are converted to the categorical data format using one-hot encoding. For each level of a categorical feature, a new variable is created. Each category is mapped with a binary variable containing either 0 or 1, with 0 representing the absence and 1 representing the presence of that category. Numeric demographic features, such as age, are also normalized.

3.2.1.3: Data Balancing using Random Over Sampling:

Data balancing refers to the process of adjusting the class distribution of a dataset to reduce class imbalance. Class imbalance occurs when one or more classes in a dataset have significantly fewer instances compared to other classes. This can lead to biased model predictions and poor performance, especially in machine learning algorithms that are sensitive to class distribution, as you can see in the class distribution graph the data is highly imbalance, so for data balancing we have adopted data over sampling technique to balance the class distribution. Before data balancing there are total 10015 images in first approach we first split dataset into train and test dataset with 80/20 ratio is this approach we have 8012 train images and 2003 test images, then perform balancing only on train dataset, after balancing image goes increase to 37646 and each class have 5378 images, but test images remains same. Data balancing is an important step in preprocessing for machine learning tasks, especially in medical or financial domains where the cost of false predictions can be high, in 2nd approach we first balanced the complete dataset and then split into train and test in this approach we have 46935 total images and 6705 images in each class.

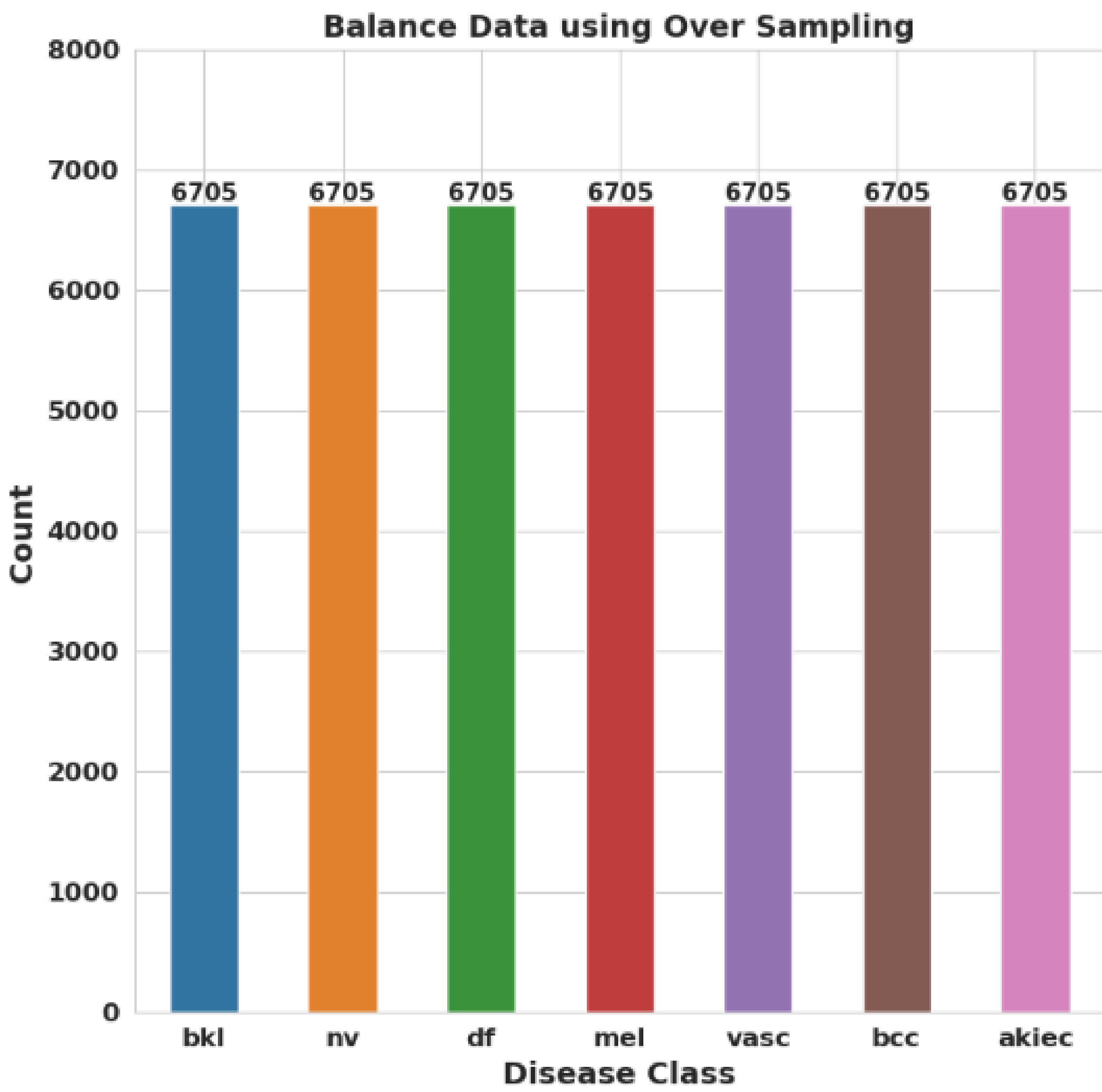

Figure 3: Data Balancing

3.2.2: Data Visualization:

Data visualization is the process of creating visual representations of data using Python libraries such as Matplotlib, Seaborn, Plotly, and others. Data visualization helps in understanding the patterns and relationships within the data by converting raw data into visual representations such as graphs, charts, histograms, scatterplots, and more. It allows us to gain insights into the data and present it in a more understandable and visually appealing way. Python's data visualization libraries provide a wide range of tools and techniques to create high-quality visualizations that can help in making better data-driven decisions, for data visualization of meta data and images matplotlib and seaborn are used.

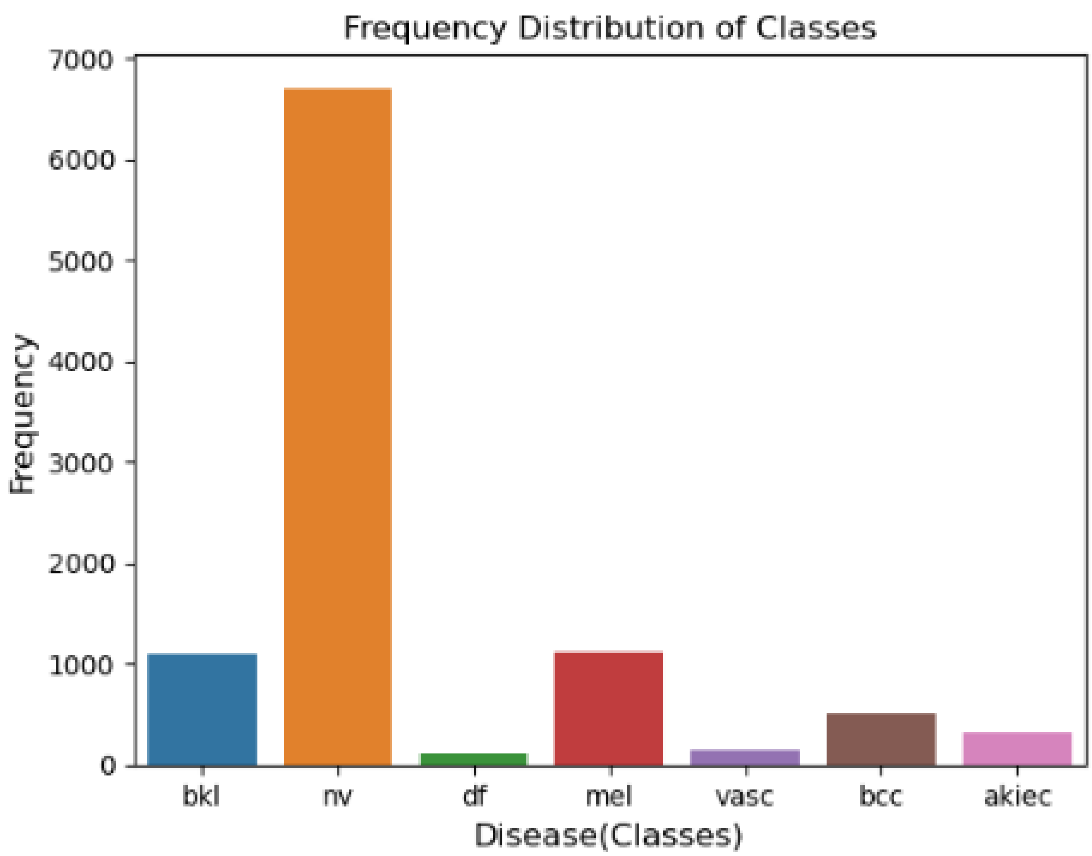

Figure 4:Skin Disesse Images Unbalanced Data

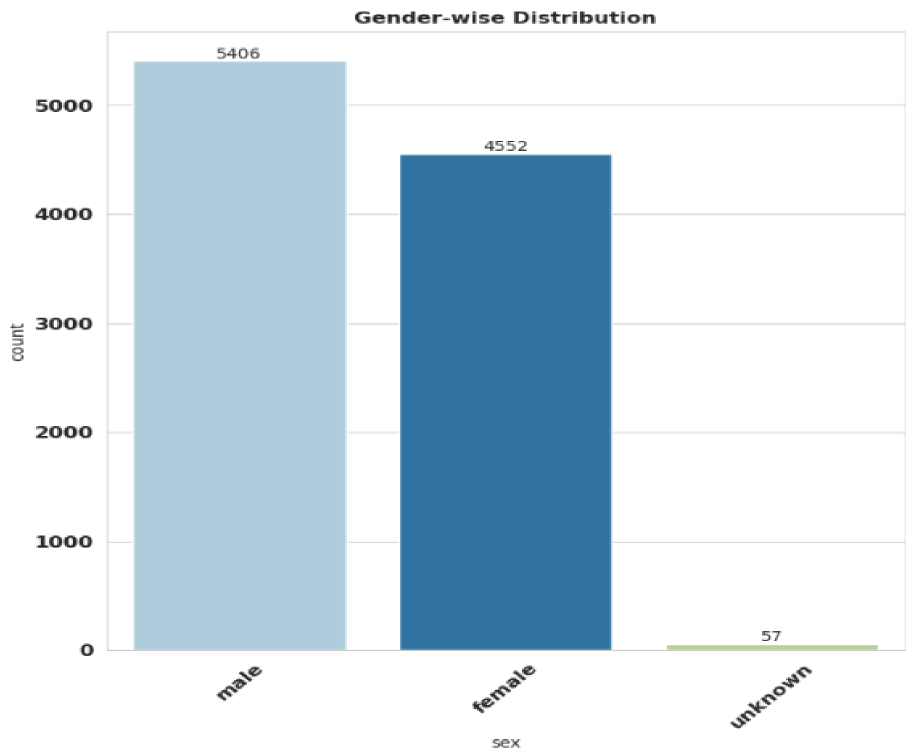

Figure 5: Gender-wise Distribution

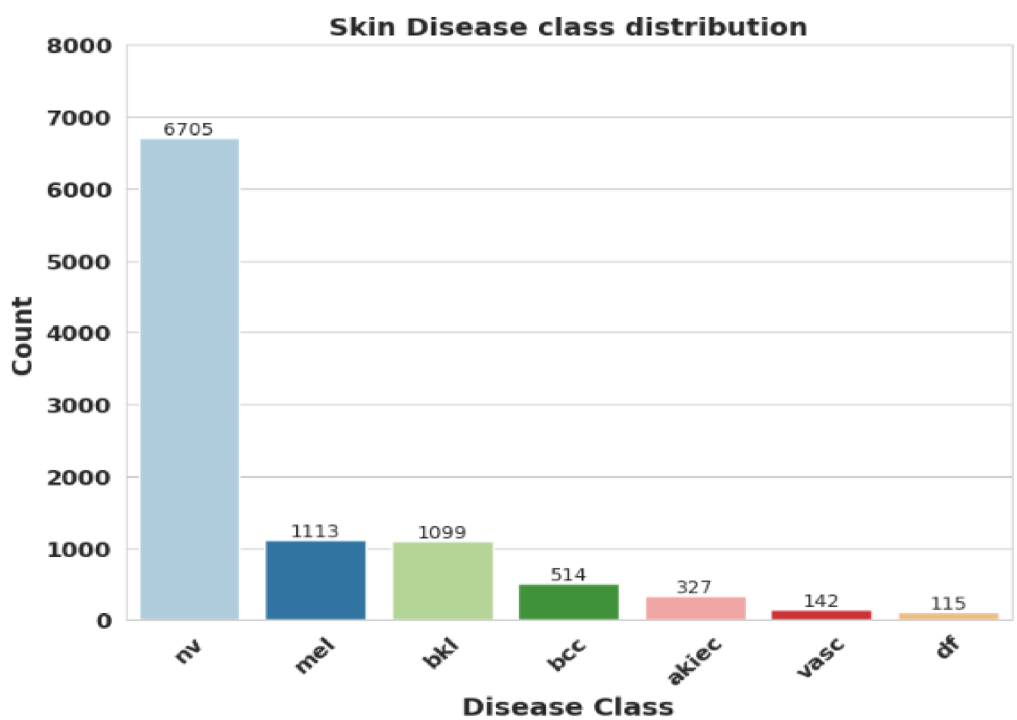

Figure 6: Skin disease calss wise distribution

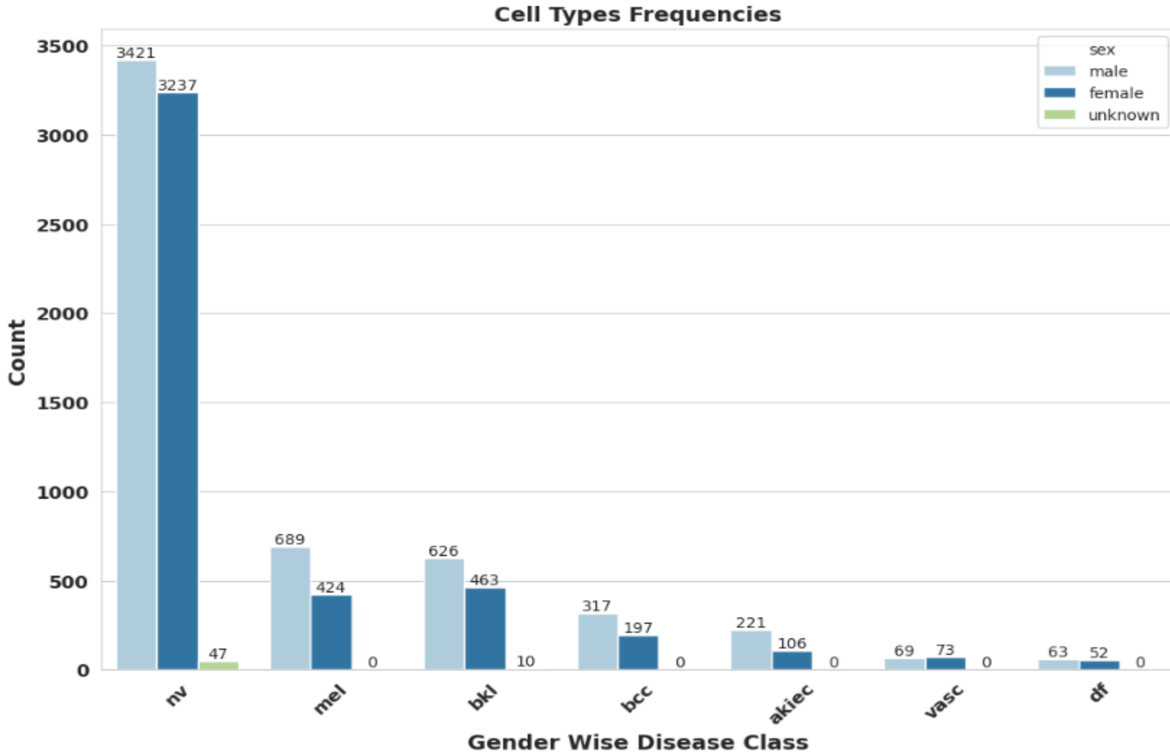

Figure 7: Gender-wise disease class distribution

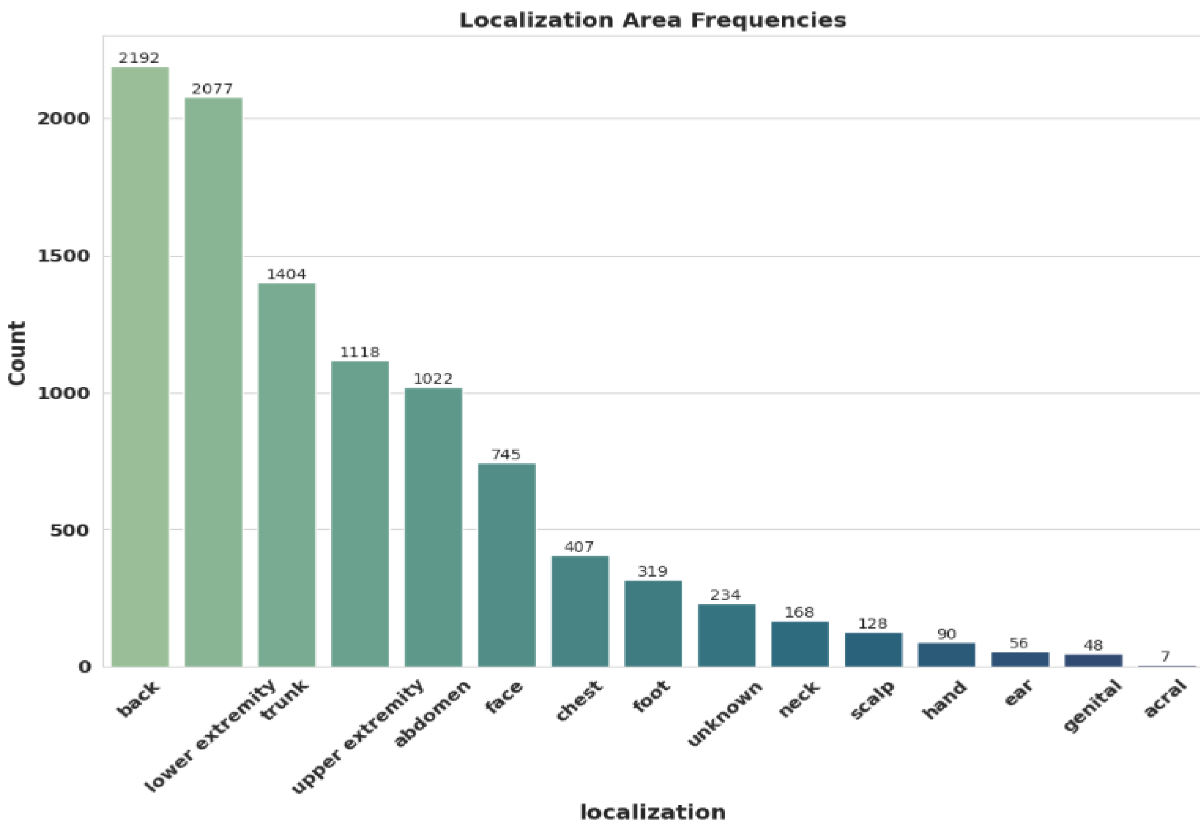

Figure 8: Disease Localization Area Frequency

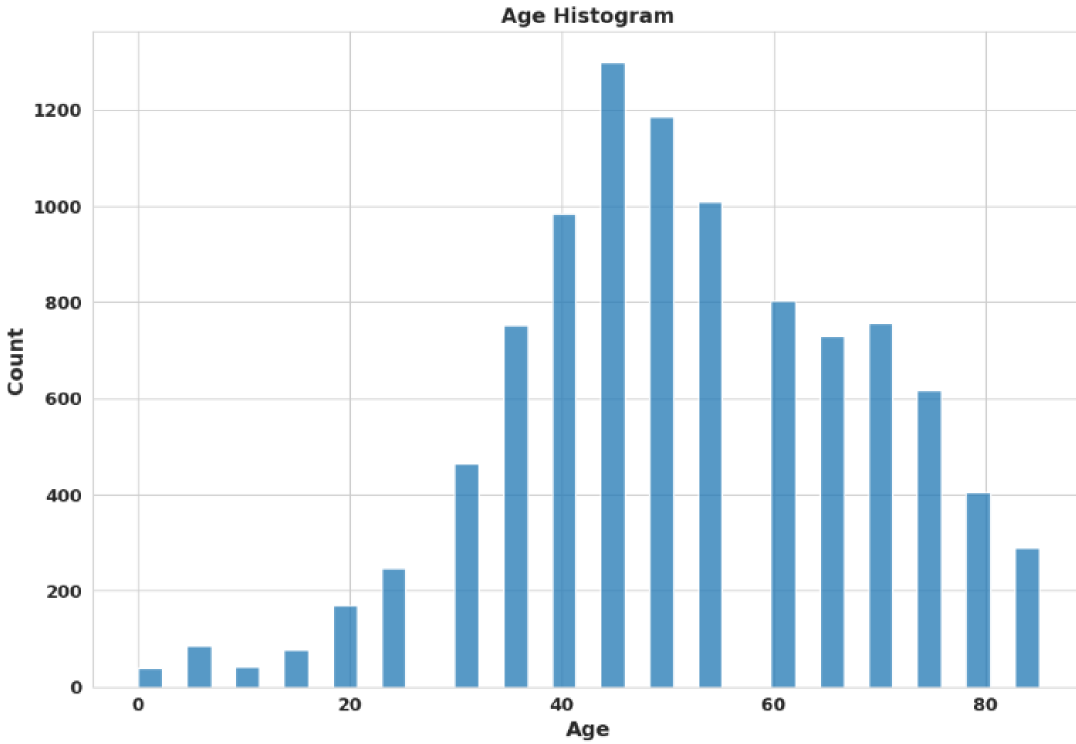

Figure 9: Age Wise Histogram

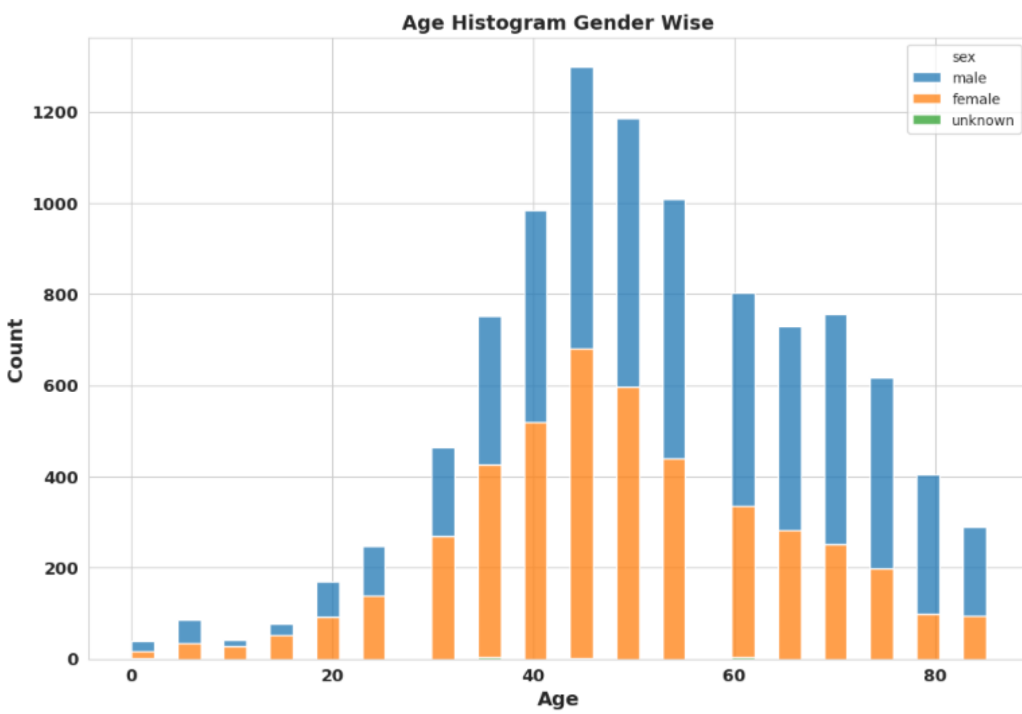

Figure 10: Gender-wise Age Histogram

3.2.3: Dataset Splitting (Train, Test):

Data splitting is the process of dividing a dataset into two or more subsets for the purpose of training and testing a machine learning model. The most common approach is to split the dataset into a training set and a testing set. The training set is used to train the model, while the testing set is used to evaluate the model's performance on unseen data. In addition to the training and testing sets, it is common to split the data further into a validation set. The validation set is used during the training process to monitor the model's performance and to fine-tune the model's hyperparameters.

Data splitting is an important step in Machine Learning(ML) because it helps to prevent overfitting, which occurs when a model is trained too well on the training data and is not able to generalize well to new, unseen data. By evaluating the model's performance on a separate testing set, we can get a better estimate of how well the model will perform on new data. In out dataset we split the complete image data set in to training, testing with the ratio of 80 & 20. There are total 10015 images, out of these 8012 images are used as training and 2003 images are used as testing data. The training data. Further 20% from the training data is used as validation data while training the model.

3.2.3: Generate Noisy Test Datasets:

In order to thoroughly assess the robustness and performance of the TRNet model on noisy test data, we have meticulously created three distinct noisy test datasets: Translational, Scaling, and Rotational.

The Translational dataset introduces variations in object position by applying random translations to the images. This enables us to evaluate how well the model can classify objects when they are shifted within the image.

The Scaling dataset involves applying random scaling transformations to the images, simulating changes in object size. By examining the model's accuracy on this dataset, we can gauge its ability to handle objects of varying scales.

The Rotational dataset introduces rotational noise by randomly rotating the images at different angles. This allows us to measure the model's capacity to accurately classify objects despite their orientation.

By incorporating these three noisy test datasets, we aim to comprehensively evaluate the TRNet model's resilience to common types of noise, providing insights into its robustness and performance in real-world scenarios.

3.3: Proposed Model:

3.3.1: Introduction to Convolution Neural Network (CNN):

A CNN, or Convolutional Neural Network, is a type of deep neural network that is commonly used for tasks such as image recognition and natural language processing. CNNs are especially good at recognizing patterns in images at different levels of abstraction. They achieve this through convolutional and pooling layers, which extract features and down sample the image data. The output is then processed by fully connected layers for final classification or regression. CNNs have many applications in industries such as healthcare, finance, retail, and entertainment, and can be used to automate tasks and improve decision-making.

3.3.2: TRNet:

The TRNet model consists of three convolution layers and four dense layers, which include an input layer, three hidden layers, and a final output layer. The model takes an RGB input image of size 28×28 and performs the convolution operation on the first three layers. In each of these layers, 3×3 sized 32 filters are applied with a ReLu activation function. This is followed by a 2D max pooling layer with a pool size of 2×2 and a batch normalization layer. In the second layer, the same convolution operation is performed with 3×3 sized 64 filters and a ReLu activation function. This is followed by a 2D max pooling layer of size 2×2 and a batch normalization layer. The third layer also performs the same convolution operation but with 3×3 sized 128 neurons and a ReLu activation function. This is followed by a 2D max pooling layer of size 2×2 and a batch normalization layer. After this, a flatten layer is applied, and the first input hidden layer of the fully connected network is implemented with 64 neurons receiving input from the flatten layer with a ReLu activation function. Then, batch normalization is applied after the activation function. The second hidden layer contains 32 neurons and is applied with a ReLu activation function, followed by a batch normalization layer. The third hidden layer contains 16 neurons and is also applied with the same activation function, followed by a batch normalization layer. Finally, the output layer is applied, which contains seven neurons representing the seven different classes, with the activation function softmax. This layer is the last classification layer of the model. The summary of the model is mention below.

Table 1: TRNet Model Summary

Layer (type)	**Output Shape**	**Param #**
Input	(None, 28, 28, 3)	0
Convolution 2D_1	(None, 28, 28, 32)	896
BatchNormalization_1	(None, 28, 28, 32)	128
MaxPooling2D_01	(None, 14, 14, 32)	0
Convolution 2D_2	(None, 14, 14, 64)	18496
BatchNormalization_2	(None, 14, 14, 64)	256
MaxPooling2D_02	(None, 7, 7, 64)	0
Convolution 2D_3	(None, 7, 7, 128)	73856
BatchNormalization_3	(None, 7, 7, 128)	512
MaxPooling2D_03	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
Dense_1	(None, 64)	131136
BatchNormalization_4	(None, 64)	256
Dense_2	(None, 32)	2080
Activation_1	(None, 32)	0
BatchNormalization_5	(None, 32)	128
Dense_3	(None, 16)	528
Activation_2	(None, 16)	0
BatchNormalization_6	(None, 16)	64
Output layer	(None, 7)	119
activation_3 (Activation)	(None, 7)	0

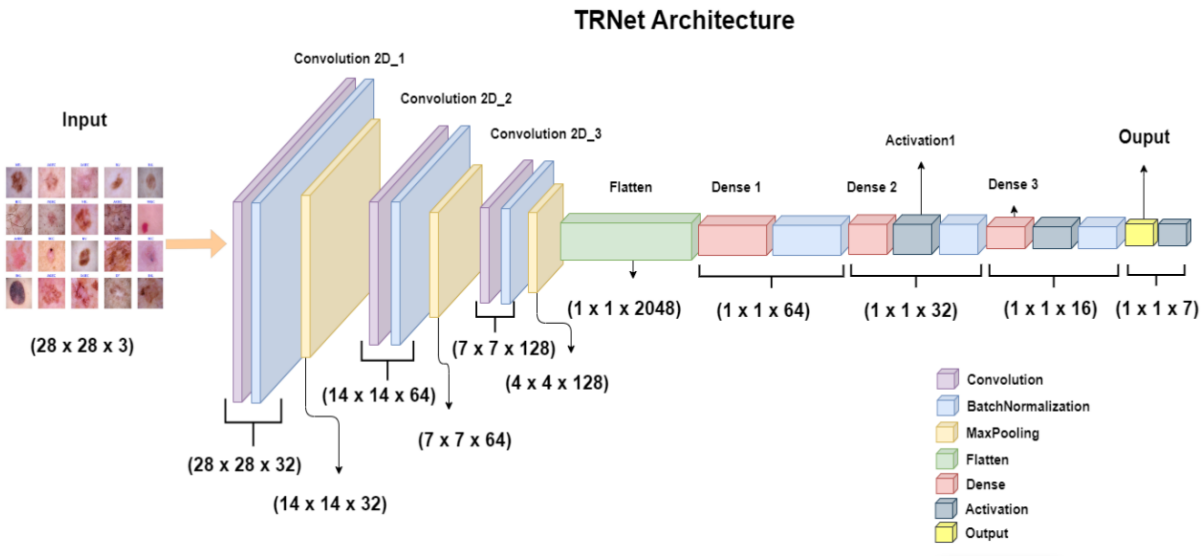

Figure 11:TRNet Architecture

3.3.3: Hybrid TRNet:

Hybrid TRNet is a novel approach that combines the TRNet algorithm with machine learning techniques such as Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression. The aim of this hybrid approach is to improve the accuracy of the TRNet algorithm by leveraging the strengths of machine learning algorithms. To ensure the best performance of the hybrid model, Grid Search Optimization techniques are applied for hyperparameter tuning. This process involves searching through a range of values for each hyperparameter and selecting the combination of hyperparameters that produces the best performance on a validation dataset. Once the best hyperparameters are identified, the machine learning algorithms are trained on the TRNet features extracted from the input data. The trained models are then used to predict the output for new data. Overall, the Hybrid TRNet approach improves the performance of TRNet by incorporating machine learning algorithms and optimizing their hyperparameters. This allows for more accurate predictions and better results in a range of applications, including image recognition, natural language processing, and other tasks that require complex data analysis.

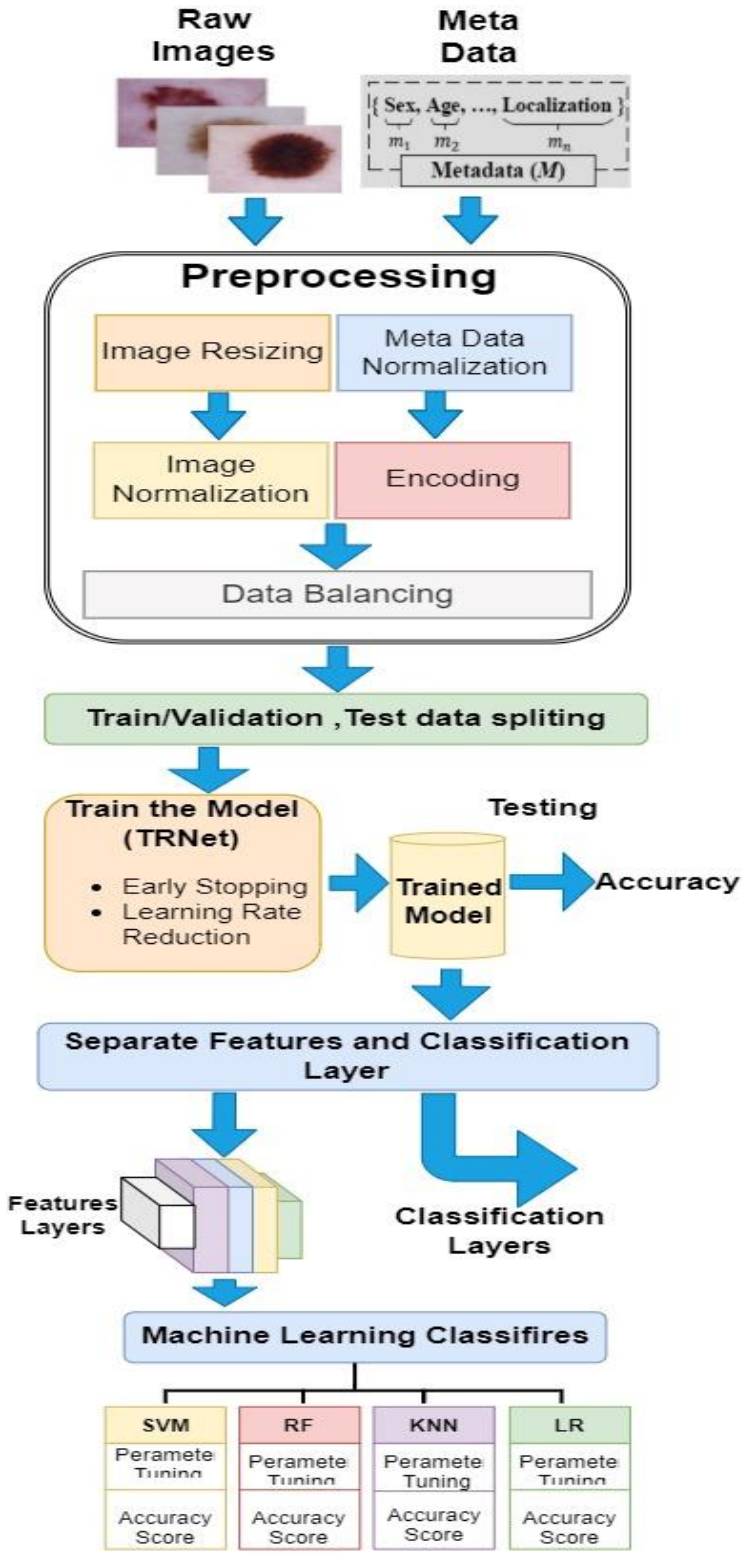

Figure 12: Proposed Models workflow

3.3.4: Training of TRNet and Hybrid TRNet Model:

The TRNet model was trained on the HAM10000 dataset in the Kaggle development environment, utilizing hardware resources such as 13 GB RAM, a maximum of 73 GB disk space, a CPU, and an NVIDIA Tesla P100 GPU. During this research we have adopt two approach, in approach 1 we first split data into training and test then perform data balancing and augmentation techniques on training data with epochs 10,20 & 30 with learning rate of 0.001 and 0.0001, while approach 2 we first balance the whole data then spitted into training and testing data training process, early stopping techniques were employed with a batch size of 64 and a maximum of 50 epochs. However, training was stopped at 21 epochs due to early stopping (**Early stopping** is a technique used during model training to prevent overfitting by stopping the training process when the performance on a validation set starts to deteriorate) criteria. The 'Adam' optimizer was used with a reduced learning rate (The **reduced learning** technique involves gradually decreasing the learning rate during the training process to improve model convergence and performance.) of lr=0.001, gradually decreased to 1.0E(-8) during training, parameters are shown in the table.

Table 2: TRNet Training Perameters

Parameters	Approach 1	Approach 2
Batch Size	64	64
Number of Epochs	10,20,30	Early Stopping max (50)
Optimizer	Adam	Adam
Learning Rate	0.001,0.0001	Reduce LR ,0.001-1.0E-8

Grid Search Optimization: Grid Search CV, or Grid Search Cross Validation, is a popular hyperparameter tuning technique used in machine learning. The goal of hyperparameter tuning is to find the best set of hyperparameters for a machine learning model to achieve the highest performance on a given dataset. Grid Search CV works by systematically searching through a grid of hyperparameters, which are combinations of different parameter values. The model is trained and evaluated on each combination of hyperparameters using cross-validation, which involves splitting the data into multiple subsets for training and testing. The performance of the model is then measured using a scoring metric, such as accuracy or mean squared error, on the validation set. The combination of hyperparameters that produces the highest performance score is then selected as the optimal set of hyperparameters for the model. Grid Search CV is a time-consuming process, as it involves training and evaluating the model on multiple combinations of hyperparameters. However, it is a powerful technique that can significantly improve the performance of a machine learning model, especially when the number of hyperparameters is small. Overall, Grid Search CV is a valuable technique for hyperparameter tuning in machine learning, as it allows for a systematic search of hyperparameters and can improve the performance of a model on a given dataset. The best optimal parameters of SVM, Random Forest, KNN & Logistic Regressions classifier are (kernel='rbf' ,C=100,gamma=0.001),(max_depth=3, max_features=1,min_samples_split=3,bootstrap=False, criterion= "entropy", n_estimators=20),(n_neighbors=1,weights='distance', metric='euclidean', algorithm= 'auto') and (C=100, penalty='l2') are respectively.

CHAPTER 4: RESULTS AND FINDINGS

4.1: Testing Environment:

All of the test are conducted in Kaggle environment.,utilizing hardware resources such as 13 GB RAM, a maximum of 73 GB disk space, a CPU, and an NVIDIA Tesla P100 GPU on well-known HAMM10000 dataset.

4.2: Experiments:

During research different Experiments was conducted with on different CNN models with different number of layers and parameters and compare the results with previous findings and other research and found that the TRNet perform well by attaining high accuracy with less number of parameters, that makes the TRNet light weight so that can be deployed on other computer systems with low specifications and Embedded systems like Raspberry pi , jetson Nano etc, the hybrid Learning approach makes the TRNet More robust by achieving the higher accuracy.

4.3: Results:

After training the CNN models (TRNet, DensNet201, and VGG16) with varying numbers of epochs (10, 20, and 30) and learning rates (0.001 and 0.0001), we observed the following results: Decreasing Test Accuracy with Increasing Epochs: Surprisingly, as we increased the number of epochs, the test accuracy of the models decreased. This suggests that training the models for an extended period did not necessarily lead to improved performance on the test dataset.
Superior Performance of TRNet at 10 Epochs: Among the three models, TRNet demonstrated the best performance when trained for 10 epochs. It outperformed both DensNet201 and VGG16 in terms of accuracy on the test dataset.

Unbalanced Training Dataset: It's worth noting that these results were obtained using an unbalanced training dataset. This implies that the dataset used for training the models had unequal representation of different classes or categories. The presence of class imbalance can affect the models' ability to accurately classify instances from underrepresented classes.

These findings highlight the importance of considering the optimal number of epochs and selecting appropriate architectures (such as TRNet) when training models on unbalanced datasets. Further investigation and experimentation may be required to identify the optimal training parameters for achieving better accuracy and handling class imbalances effectively.

Table 3:Accuracy Score Original Test Data, unbalance Training

Original Test Data, unbalance Training				
Epochs	Learning Rate	TRNet	DensNet201	VGG16
10	0.001	**75.09**	72.99	71.24
20	0.001	74.39	72.99	70.69
30	0.001	73.24	74.14	58.31
10	0.0001	71.99	71.24	69
20	0.0001	73.09	71.89	70.59
30	0.0001	72.04	73.99	71.24

TRNet with Hybrid Learning Approach:

By adopting a hybrid learning approach, we incorporated four machine learning algorithms (SVM, KNN, RF, and LR) with TRNet to enhance its performance and accuracy. Through experimentation, we observed that TRNet, when combined with SVM and LR, exhibited superior performance compared to the other algorithms.

These findings indicate that the hybrid learning approach, integrating TRNet with SVM and LR, significantly improved the accuracy of the model. By leveraging the strengths of both Deep.learning (TRNet) and traditional machine learning algorithms, we were able to achieve enhanced classification accuracy.

Therefore, it can be concluded that the hybrid learning approach, involving the combination of TRNet with SVM and LR, effectively increases the accuracy of the model. This approach demonstrates the potential to obtain improved results by synergistically leveraging the capabilities of both Deep.learning and traditional machine learning techniques.

Table 4:TRNet Hybrid Original Test Data, unbalance Training

TRNet Hybrid Original Test Data, unbalance Training			
TRNet	10	0.001	75.09
TRNet + SVM	10	0.001	**76.38**
TRNet + KNN	10	0.001	71.64
TRNet + RF	10	0.001	68.34
TRNet + LR	10	0.001	**76.43**

Accuracy of DensNet201 with Hybrid Learning Approach:

When applying a hybrid learning approach to DensNet201 by combining it with machine learning classifiers, we observed that it did not perform as well as TRNet. The results obtained from the experiment indicated lower accuracy levels compared to TRNet with the same hybrid learning setup.

Although DensNet201 is a powerful convolutional neural network architecture, it seems that the integration of machine learning classifiers did not lead to significant improvements in its performance. It is important to note that the performance of hybrid learning approaches can vary depending on the specific architecture and the combination of classifiers used.

While TRNet demonstrated improved accuracy when combined with SVM and LR, it is possible that DensNet201 may benefit from alternative machine learning classifiers or different hybrid learning techniques to enhance its performance. Further experimentation and exploration of different configurations may be required to optimize the hybrid learning approach for DensNet201.

Table 5:DensNet201 Hybrid Original Test Data, unbalance Training

DensNet201	10	0.001	72.99
DensNet201+ SVM	10	0.001	71.8407
DensNet201 + KNN	10	0.001	66.1
DensNet201 + RF	10	0.001	66.25
DensNet201+ LR	10	0.001	71.939

Accuracy of VGG16 with Hybrid Learning Approach:

During the analysis of VGG16 with a hybrid learning approach, combining it with machine learning classifiers, we found that its performance was not satisfactory. The results obtained from the experiment indicated that the accuracy of VGG16 did not significantly improve when utilizing the hybrid learning setup.

VGG16 is a widely used convolutional neural network architecture known for its deep layer structure. However, when integrated with machine learning classifiers, it did not demonstrate notable advancements in accuracy.

It is important to note that the success of hybrid learning approaches can vary depending on the specific architecture and the choice of classifiers. While TRNet showed promising results with SVM and LR, and DensNet201 may require alternative classifiers or different hybrid learning techniques, VGG16 may also require different approaches to optimize its performance when combined with machine learning classifiers.

Further experimentation and exploration of alternative combinations or techniques may be necessary to achieve better accuracy and performance with VGG16 and the hybrid learning approach.

Table 6:VGG16 Hybrid Original Test Data, unbalance Training

VGG16 Hybrid Original Test Data, unbalance Training				
VGG16	10	0.001	71.24	
VGG+ SVM	10	0.001	66.3	
VGG + KNN	10	0.001	66.2506	
VGG + RF	10	0.001	68.197	
VGG+ LR	10	0.001	**71.293**	

Performance analysis with Noisy Test Data:

We conducted performance testing and analysis of TRNet, DenseNet201, and VGG16 on noisy datasets containing variations in translation, scaling, and rotation. From the results displayed in the table, it is evident that the accuracy of the models decreased when exposed to the noisy datasets.

Interestingly, TRNet demonstrated superior performance specifically on the scaling noisy dataset. Despite the overall decrease in accuracy, TRNet was able to maintain a relatively higher accuracy compared to DenseNet201 and VGG16 when faced with scaling variations in the data.
These findings suggest that TRNet is more robust and capable of handling scaling noise, whereas the performance of DenseNet201 and VGG16 may be more affected by such variations in the dataset.
It is important to consider these results when selecting a model for tasks involving noisy datasets, as the performance characteristics of each model may differ depending on the type of noise introduced.
Further investigation and analysis may be necessary to understand the underlying reasons for TRNet's superior performance on scaling noisy datasets and to optimize the models' performance in the presence of different types of noise.

Table 7:Models Performance on Noisy Test datasets

Noise Test Data, unbalance Training					
	Epochs	Learning Rate	TRNet	DensNet201	VGG16
Original Test Data	10	0.001	**75.09**	72.99	71.24
Translation Noise	10	0.001	34.45	61.01	63.8
Scalling and Cropping	10	0.001	63.16	60.01	63.31
Rotational Noise	10	0.001	28.26	59.76	63.31

Performance Analysis of Hybrid TRNet on Noisy Test Data:

We conducted performance testing and analysis of TRNet and a hybrid version of TRNet with original and noisy datasets. Our findings indicate that TRNet, when combined with the Random Forest (RF) machine learning algorithm, performed well on the noisy test data.
When comparing the performance of TRNet and the hybrid TRNet on both the original and noisy datasets, it was observed that the hybrid TRNet, particularly with the RF algorithm, exhibited good performance when tested with the noisy dataset.

This suggests that the combination of TRNet and the RF algorithm improved the model's ability to handle and classify instances in the presence of noise. It is worth noting that TRNet alone also demonstrated promising results on the original dataset, indicating its effectiveness in general image classification tasks.

These findings emphasize the potential of hybrid learning approaches, specifically combining TRNet with the RF algorithm, to enhance the model's performance on noisy test data. Further exploration and experimentation can help optimize the hybrid TRNet approach and investigate its robustness in different noisy scenarios.

Table 8:Performance Analysis on original and Noisy Test datasets, Unbalance Training

Hybrid TRNet ,Noise Test Data, unbalance Training									
	Epoches	**Learning Rate**	**orignal**	**Translation Noise**	**Noise Ratio**	**Scalling and Cropping**	**Noise Ratio**	**Rotational Noise**	**Noise Ratio**
TRNet	10	0.001	75.09	34.45	0.458782794	63.16	0.841123985	28.26	0.376348382
TRNet + SVM	10	0.001	76.38	44.88	0.597682781	63.65	0.847649487	26.26	0.349713677
TRNet + KNN	10	0.001	71.64	43.18	0.575043281	58.06	0.773205487	25.46	0.339059795
TRNet + RF	10	0.001	**68.34**	**65.75**	**0.875615928**	**66.65**	**0.887601545**	**66.4**	**0.884272207**
TRNet + LR	10	0.001	76.43	42.23	0.562391797	**62.45**	**0.831668664**	21.8172	0.290547343

To further analyze the performance of the Hybrid TRNet model on noisy test data, we experimented with reducing the learning rate from 0.001 to 0.0001. From the results observed in the table, it can be concluded that reducing the learning rate resulted in a decrease in overall accuracy.

However, despite the decrease in accuracy, the results on the noisy test dataset showed a slight improvement compared to the original learning rate. In particular, the Hybrid TRNet model combined with the Random Forest (RF) classifier continued to perform well compared to other machine learning classifiers.

These findings suggest that reducing the learning rate may help the model better adapt and generalize to the noisy test data, resulting in improved performance. Although the overall accuracy decreased, the model's ability to handle noise was enhanced.

It is important to note that the optimal learning rate may vary depending on the dataset and task at hand. Further experimentation and fine-tuning of the learning rate can help optimize the performance of the Hybrid TRNet model on both original and noisy datasets.

Table 9:Performance of TRNet on Noisy test dataset with lr 0.0001, Unbalance Training

	Hybrid TRNet ,Noise Test Data, unbalance Training, Lrn=0.0001								
	Epochs	Learning Rate	orignal	Translation Noise	Noise ratio	Scalling and Cropping	Noise ratio	Rotational Noise	Noise ratio
TRNet	10	0.0001	71.99	21.92	0.304486734	63.55	0.882761495	22.62	0.314210307
TRNet + SVM	10	0.0001	73.789	22.616	0.314154744	61.8	0.858452563	8.6869	0.120668148
TRNet + KNN	10	0.0001	68.29	45.332	0.629698569	61.85	0.859147104	34.34	0.477010696
TRNet + RF	10	0.0001	68.347	**66.301**	**0.920975135**	**67.249**	**0.934143631**	**66.4**	**0.922350326**
TRNet + LR	10	0.0001	73.53	19.87	0.276010557	65.1023	0.904324212	16.1757	0.224693707

Performance Analysis of Hybrid TRNet on Balanced Training Data:

In order to analyze the performance of TRNet on balanced training data, we implemented various data balancing techniques, along with data augmentation. The results indicate that these techniques contribute to enhancing the model's accuracy.

Data balancing techniques, such as oversampling minority classes, undersampling majority classes, or using synthetic data generation methods, help address class imbalance in the training data. By ensuring a more equal representation of different classes, the model becomes better equipped to learn and generalize across all classes.

Additionally, data augmentation techniques, such as random rotations, translations, flips, or adding noise, increase the diversity and variability of the training data. This, in turn, helps the model to better handle variations and improves its ability to generalize to unseen data.

The combination of data augmentation and data balancing techniques has proven effective in enhancing the accuracy of the Hybrid TRNet model. These techniques provide the model with a more comprehensive and balanced training set, allowing it to learn from a wider range of instances and improve its overall performance.

Therefore, it can be concluded that applying data augmentation and data balancing techniques to TRNet can significantly enhance the model's accuracy and improve its ability to handle class imbalances.

Table 10:TRNet accuracy score on balanced and unbalanced Training data

Hybrid TRNet on Data Balancing (Accuracy)						
	Epochs	Learning Rate	original Training	Augmentation	Random Over Sampling	Adaptive
TRNet	10	0.001	**71.99**	**74.94**	**73.69**	**71.49**
TRNet + SVM	10	0.001	73.789	75.28	71.84	68.2476
TRNet + KNN	10	0.001	68.29	71.44	75.28	67.29905
TRNet + RF	10	0.001	68.3474	68.84	60.609	57.2641
TRNet + LR	10	0.001	73.53	75.486	71.39	67.34897

Performance Analysis of Hybrid TRNet on Complete Balanced Data:

Now, we will adopt another approach to test and analyze the performance of the model. In this technique, we will perform full data balancing by using the random oversampling technique. Firstly, we will balance the entire dataset, which includes both the training and testing data. Then, we will split the balanced dataset into separate training and testing sets.

By employing random oversampling, we aim to address the class imbalance issue present in the original dataset. This technique involves randomly duplicating instances from the minority classes until they are represented at a similar level as the majority class. This ensures a more balanced distribution of classes in the dataset.

Once the data is balanced, we will split it into training and testing sets to evaluate the performance of the model on the balanced data. This approach allows us to assess how well the model performs when trained and tested on a more representative and balanced dataset.

By utilizing this technique, we expect to see improved performance and accuracy of the model, as it will be trained and evaluated on a more balanced and fair dataset.

Model Training:

TRNet model is trained with parameters mention as above table, below figure shows the training and validation scores with respect to the number of epochs.

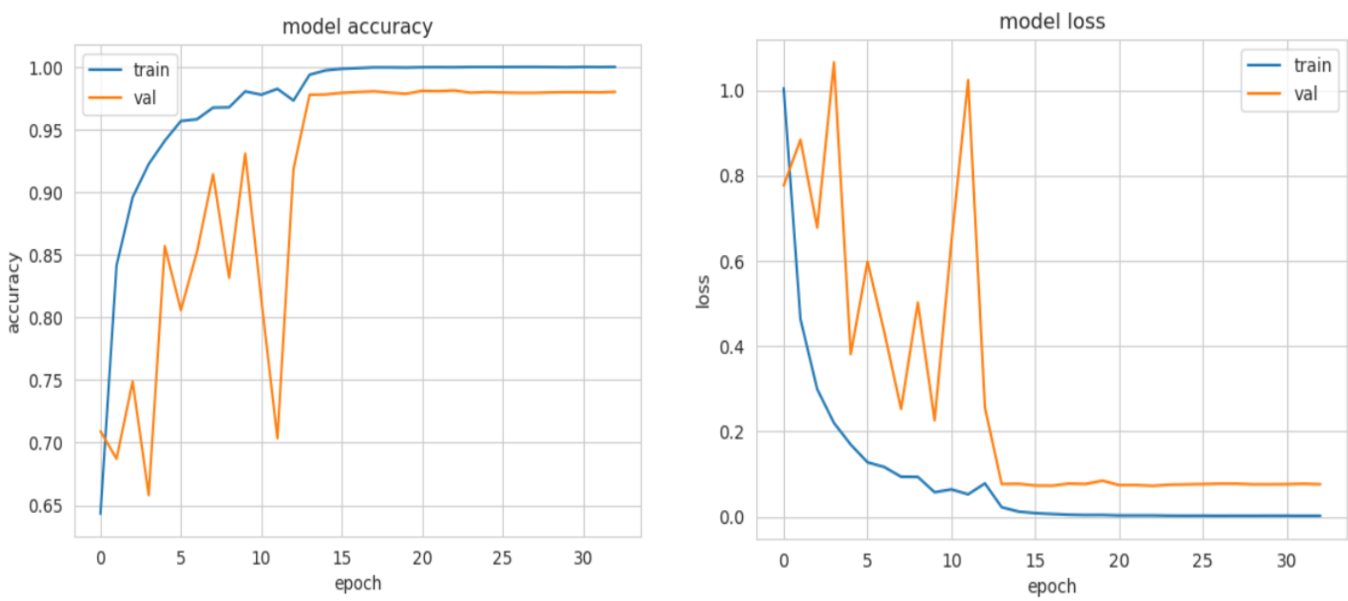

Figure 13:TRNet Training Accuracy and loss Score

KFold Validation: KFold cross-validation is a technique used to evaluate the performan ce of a machine learning model. It involves dividing the dataset into k equally-sized folds or subsets. The model is trained and evaluated k times, with each fold serving as the vali dation set once, while the remaining k-1 folds are used for training. By repeating this pro cess k times, the model is assessed on different subsets of the data, providing a more com prehensive understanding of its performance. KFold cross-validation helps to mitigate the impact of data variability and overfitting, and provides a more reliable estimate of the m odel's performance by averaging the results across multiple iterations. It is a valuable tech nique for assessing how well the model generalizes to unseen data and gaining insights in to its robustness and performance across different subsets of the dataset. I have applied K -Fold cross validation with number of Folds K=5.

Correlation Matrix:

A correlation matrix is a square matrix that contains correlation coefficients between pair s of variables in a dataset. It helps quantify the strength and direction of the linear relation ship between variables. The coefficients range from -1 to 1, indicating the degree of corre lation. A value of 1 represents a perfect positive correlation, -1 represents a perfect negati ve correlation, and 0 represents no correlation. Correlation matrices are useful for identify ing patterns and associations between variables, aiding in feature selection, dimensionalit y reduction, and understanding data relationships. Heatmaps can be used to visualize the c orrelation matrix, with colors representing the strength of correlations. When applied to a dataset of 7 skin cancer disease classes, the correlation matrix and heatmap can provide in sights into the relationships between the classes, assisting in research, diagnosis, and treat ment strategies. It's important to note that correlation does not imply causation.

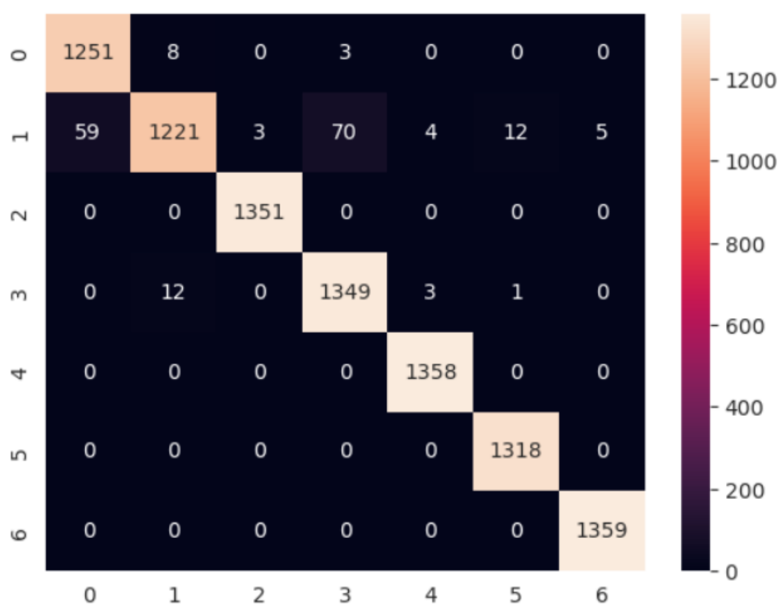

Figure 14: Feature Correlation Matrix

TRNet Model Evaluation Score:

The TRNet model was evaluated on a 20% test dataset, resulting in a test loss of 0.07440 and an accuracy score of 98.08%. Class-wise results are also predicted with accu racy, precision, recall, and F1-score. Additionally, k-fold cross-validation was applied wit h k=5 folds to further assess the model's performance, the class wise results are mention i n below table.

Hybrid TRNet Evaluation Score:

	precision	recall	f1-score	support
Actinic keratoses and intraepithelial carcinomae	1.00	1.00	1.00	1359
basal cell carcinoma	0.99	1.00	1.00	1318
benign keratosis-like lesions	0.95	0.99	0.97	1262
dermatofibroma	1.00	1.00	1.00	1351
melanocytic nevi	0.98	0.89	0.93	1374
pyogenic granulomas and hemorrhage	0.99	1.00	1.00	1358
melanoma	0.95	0.99	0.97	1365
accuracy			0.98	9387
macro avg	0.98	0.98	0.98	9387
weighted avg	0.98	0.98	0.98	9387

Table 11:TRNet Classification Report

The TRNet Hybrid Model combines the TRNet model with various traditional machine learning algorithms, namely SVM, Random Forest, KNN, and Logistic Regression. This hybrid approach aims to leverage the strengths of both Deep.learning and traditional machine learning methods.

To optimize the performance of the hybrid model, hyperparameter tuning is performed using the Grid Search CV technique. Grid Search CV systematically explores a predefined grid of hyperparameters to find the best combination that maximizes the model's performance. This process helps in finding the optimal values for hyperparameters such as learning rate, regularization strength, number of estimators, and neighbor count, depending on the specific algorithm.

In addition, K-fold cross-validation with k=5 folds is applied to evaluate the hybrid model's accuracy score. K-fold cross-validation involves splitting the dataset into k equal parts (folds) and iteratively training and evaluating the model on different combinations of folds. By averaging the results across the folds, a more robust estimation of the model's accuracy can be obtained, reducing the impact of data variability.

By combining the TRNet model with traditional machine learning algorithms, performing hyperparameter tuning with Grid Search CV, and utilizing K-fold cross-validation, the hybrid model aims to achieve improved accuracy in predicting the target variable. The specific accuracy score can be obtained by evaluating the model on the test set or through further analysis of the experimental results, the over all results are mention in below table.

TRNet with SVM:

SVM Accuracy: 98.87%

KFold Cross validation Results: No of Folds= 5, the accuracies of all 5 folds are 100.0% , 99.986%, 100.0%, 100.0% and 98.122% are respectively.

Class wise Results:

Table 12:TRNet+SVM Classification Report

	precision	recall	f1-score	support
Actinic keratoses and intraepithelial carcinomae	1.00	1.00	1.00	1359
basal cell carcinoma	1.00	1.00	1.00	1318
benign keratosis-like lesions	0.98	0.99	0.98	1262
dermatofibroma	1.00	1.00	1.00	1351
melanocytic nevi	0.98	0.94	0.96	1374
pyogenic granulomas and hemorrhage	1.00	1.00	1.00	1358
melanoma	0.97	0.99	0.98	1365
accuracy			0.99	9387
macro avg	0.99	0.99	0.99	9387
weighted avg	0.99	0.99	0.99	9387

TRNet with Random Forest:

Results: Random Forest Classifier Accuracy: 96.6549 %

KFold Cross validation Results: No of Folds= 5, the accuracies of all 5 folds are 99.72% , 99.76%, 99.53%, 99.82% and 96.99% are respectively.

Class wise Results:

Table 13:TRNet+Random Forest Classification Report

	precision	recall	f1-score	support
Actinic keratoses and intraepithelial carcinomae	1.00	1.00	1.00	1359
basal cell carcinoma	0.99	1.00	0.99	1318
benign keratosis-like lesions	0.94	0.98	0.96	1262
dermatofibroma	1.00	1.00	1.00	1351
melanocytic nevi	0.98	0.87	0.93	1374
pyogenic granulomas and hemorrhage	1.00	1.00	1.00	1358
melanoma	0.93	0.98	0.95	1365
accuracy			0.98	9387
macro avg	0.98	0.98	0.98	9387
weighted avg	0.98	0.98	0.98	9387

TRNet with KNN:

Results: KNN Accuracy: 99.12 %

KFold Cross validation Results: No of Folds= 5, the accuracies of all 5 folds are 99.96% , 99.94%, 99.98%, 99.98% and 98.04% are respectively.

Class wise Results:

Table 14:TRNet+KNN Classification Report

	precision	recall	f1-score	support
Actinic keratoses and intraepithelial carcinomae	1.00	1.00	1.00	1359
basal cell carcinoma	1.00	1.00	1.00	1318
benign keratosis-like lesions	0.96	1.00	0.98	1262
dermatofibroma	1.00	1.00	1.00	1351
melanocytic nevi	1.00	0.92	0.96	1374
pyogenic granulomas and hemorrhage	1.00	1.00	1.00	1358
melanoma	0.96	1.00	0.98	1365
accuracy			0.99	9387
macro avg	0.99	0.99	0.99	9387
weighted avg	0.99	0.99	0.99	9387

TRNet with Logistic Regression:

Results: Logistic Regression Classifier **Accuracy**: 98.4233 %

KFold Cross validation Results: No of Folds= 5, the accuracies of all 5 folds are 100% , 99.98%, 100.0%, 99.98% and 97.97% are respectively.

Class wise Results:

Table 15:TRNet+Logistic Regression Classification Report

	precision	recall	f1-score	support
Actinic keratoses and intraepithelial carcinomae	1.00	1.00	1.00	1359
basal cell carcinoma	1.00	1.00	1.00	1318
benign keratosis-like lesions	0.96	0.99	0.97	1262
dermatofibroma	1.00	1.00	1.00	1351
melanocytic nevi	0.99	0.92	0.95	1374
pyogenic granulomas and hemorrhage	1.00	1.00	1.00	1358
melanoma	0.95	0.98	0.97	1365
accuracy			0.98	9387
macro avg	0.98	0.98	0.98	9387
weighted avg	0.98	0.98	0.98	9387

TRNet is Combined with other machine learning models like SVM, Random Forest , K-Nearest Neighbor and found that TRNet with KNN perform well with respect to SVM, Random Forest and Logistic Regression, by achieving 99.12 % accuracy, the results are mentioned in blow table.

Table 16:TRNet and Hybrid TRNet Accuracy Score

Model	**TRNet**	**TRNet+SVM**	**TRNet+RF**	**TRNet+KNN**	**TRNet+LR**
Accuracy	98.08%	98.87%	96.65 %	99.12 %	98.42 %

CHAPTER 5: CONCLUSION

During the research, several experiments were conducted on different CNN models with varying numbers of layers and parameters. The results were compared with previous findings and other research studies. TRNet consistently outperformed DensNet201 and VGG16 across different epochs and learning rates. It achieved the highest accuracy in most cases. With a total of 228,455 parameters, TRNet proves to be a lightweight model that can be easily deployed on computer systems with low specifications and embedded systems like Raspberry Pi and Jetson Nano.

To further enhance the performance and robustness of TRNet, a hybrid learning approach was employed with balanced and unbalanced techniques. The TRNet model was combined with other machine learning models, including SVM, Random Forest, K-Nearest Neighbor (KNN), and Logistic Regression. Adding SVM to the TRNet hybrid model resulted in a slightly higher accuracy of 76.38% compared to the base TRNet model. The TRNet hybrid model with LR performed well, achieving an accuracy of 76.43%, slightly higher than the base TRNet model.

We took a new approach to assess the performance of the model. We applied full data balancing by utilizing random oversampling techniques to address class imbalance. The balanced dataset was then split into separate training and testing sets, we conclude that TRNet and TRNet with KNN achieves the remarkable accuracy of 98.08% and 99.12% respectively,We evaluated the model's performance on the balanced data, aiming to enhance accuracy and fairness. Additionally, the model's robustness was tested on noisy datasets with variations in translation, scaling, and rotation, providing insights into its ability to handle real-world scenarios with different types of noise. We test and analyze the model performance on noisy test datasets, TRNet and TRNet with KNN perform very well on scaling noisy test dataset.

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