**TRNet: A Novel Lightweight Hybrid Learning Approach for Skin Disease Image Classification**

**Material & Method:**

**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. 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 and gender, lesion diagnosis, and the skin lesion directory. The second and more critical part of the data set consists of visual files. 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 and upper limbs. Solar Lentigo is a type of hyper-pigmented infection 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 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, and lower leg.

**Melanocytic Nevi (nv):**

There are seven subclasses in the database that encompass all of the benign skin tumours known as melanocytic nevi, 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.

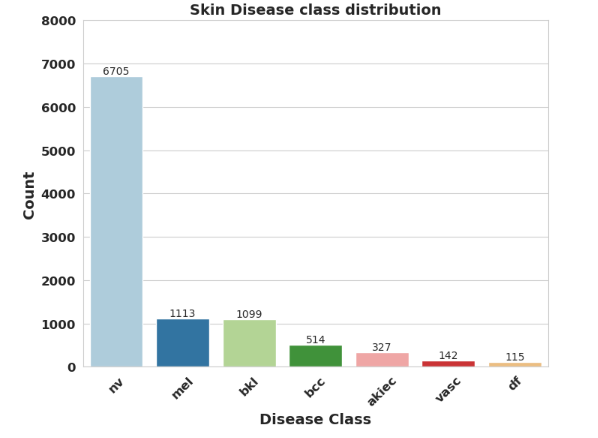
**Vascular Lesions (vasc):**

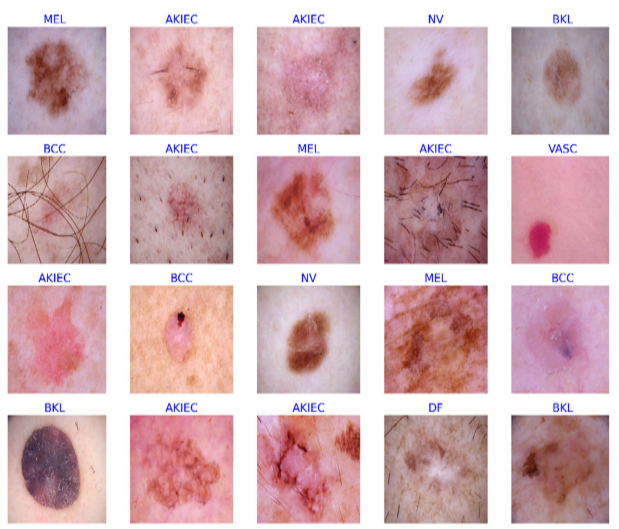
Most cases of vascular lesions (vasc) are hereditary, but they can also develop later in life and are typically benign. These lesions can take on a variety of appearances and are characterized by the formation of sores on the skin and surrounding tissues. They are sometimes referred to as birthmarks.

**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.

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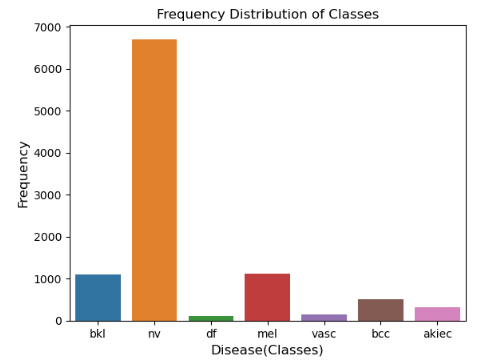
**Proposed Methodology:**

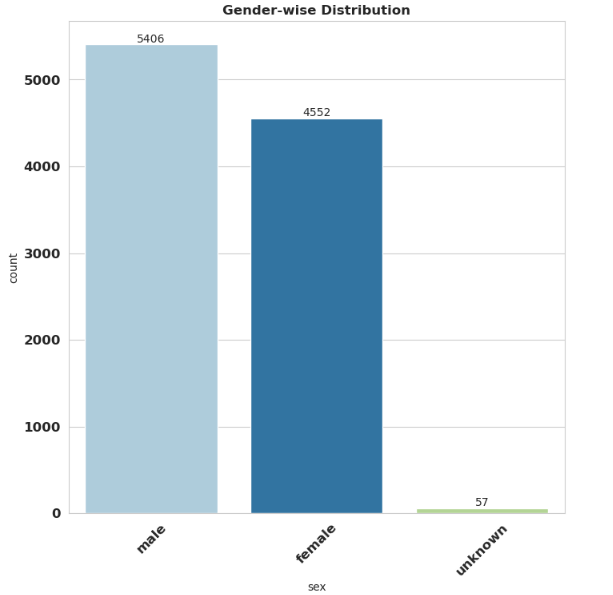
**Data Preprocessing:**

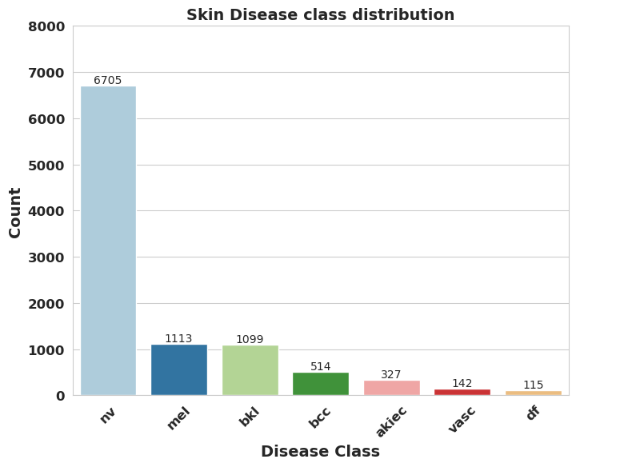
**Image Preprocessing:** Image Pre-processing is a crucial step in working with clinical image data, particularly for training convolutional neural network (CNN) based systems. In this study, the authors aimed to improve the generalizability of their CNN design and reduce time-consuming preprocessing 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].

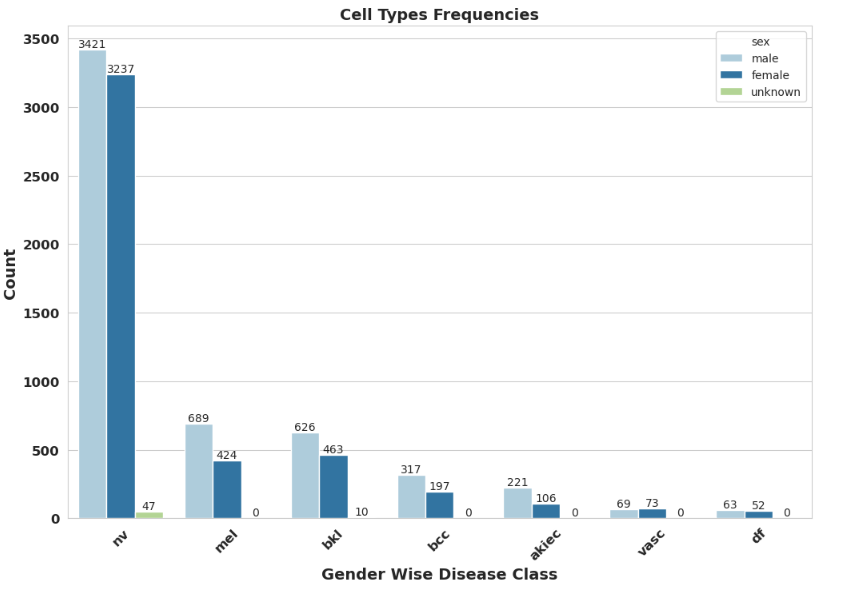
**Meta-Data Preprocessing** **(Data Cleaning & Normalization):** This paragraph describes the metadata pre-processing step. This step involves removing any missing data from the clinical information. Since most demographic features are categorical variables represented as strings or categories, they 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.

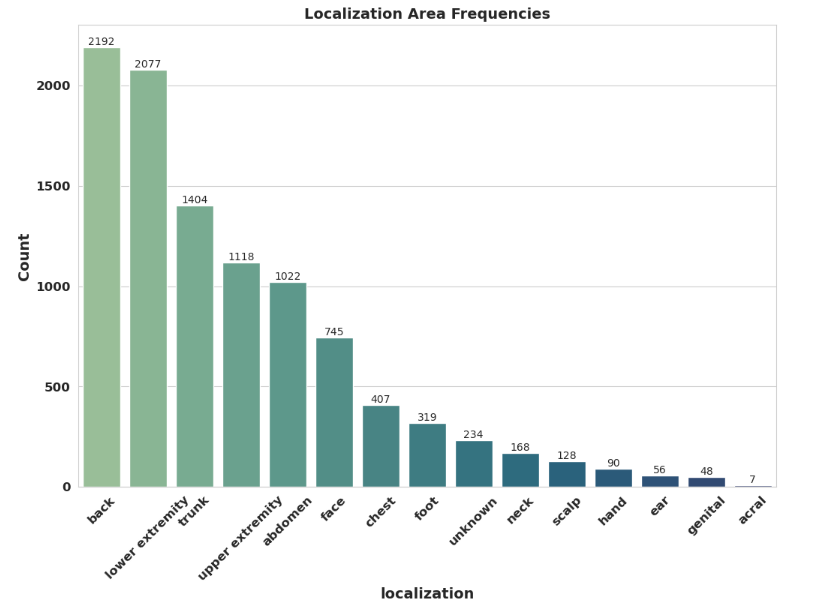
**Data Visualization:** Data visualization is the process of creating visual representations of data using Python libraries such as Matplotlib, Seaborn, Plotly, and others. Data visualization helps in understanding the patterns and relationships within the data by converting raw data into visual representations 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.

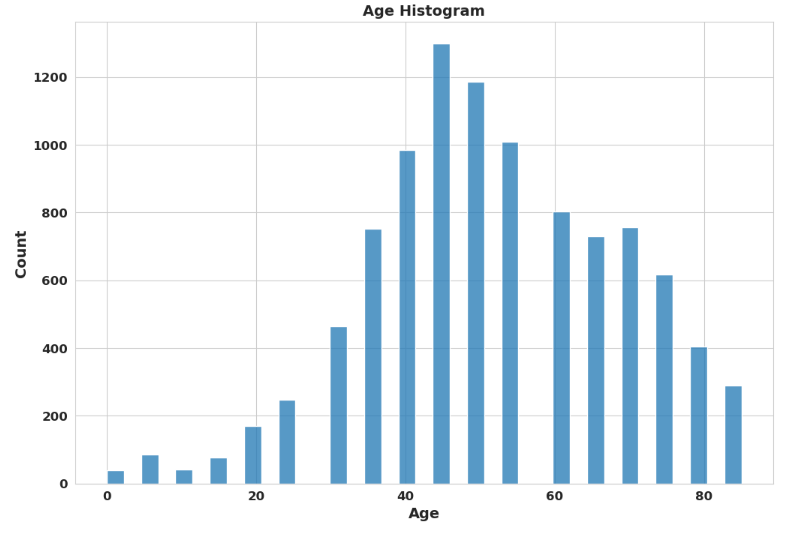
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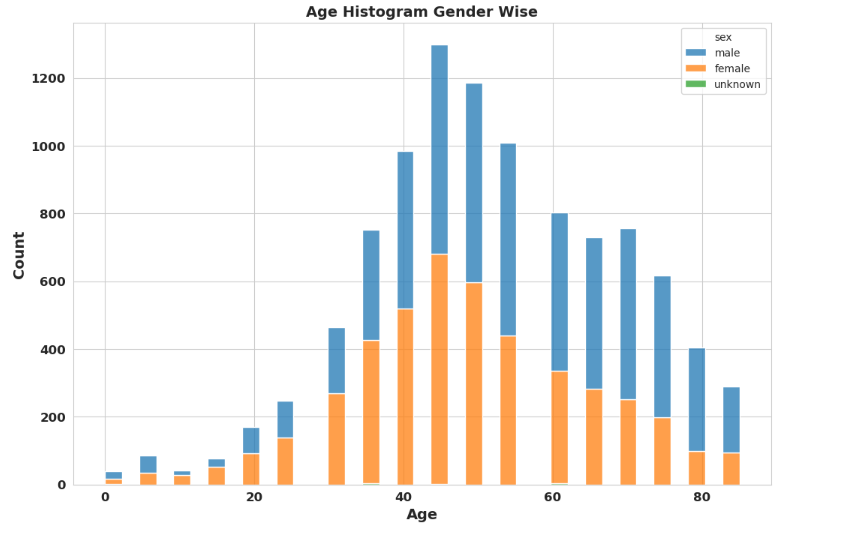
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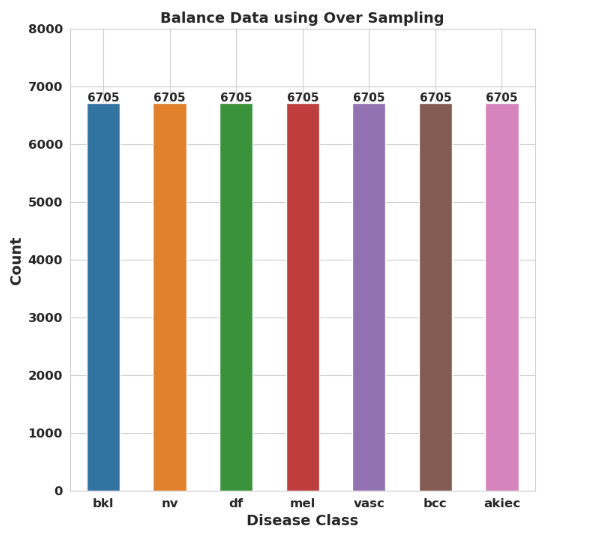
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**Data Balancing:** Data balancing refers to the process of adjusting the class distribution of a dataset to reduce class imbalance. Class imbalance occurs when one or more classes in a dataset have significantly fewer instances compared to other classes. 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, after balancing image goes increase to 46935 and each class have 6705 images. 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.



**Data Splitting:** 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 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 46935 images ,out of this 37548 images are used as training and 9387 images are used as testing data. The training data. Further 20% from the training data is used as validation data while training the model.

**Image Downsampling:** The dataset consists of two main components. The first is a metadata file containing specific information about cancer lesion images, such as the location of the skin lesion, patient age and gender, diagnosis of the lesion, and the directory for the skin lesion. The second and more important section of the dataset is made up of visual files. The objective of this study is to classify skin lesions based solely on digital images. To accomplish this, the data file was reorganized to include only the lesion type and image file directory, and each lesion's textual label was transformed into a digital value between 0 and 6.The original dermoscopic images in the dataset have a resolution of 600 x 450 pixels and are saved in the RGB format. However, it was found that processing time increases with larger image sizes. Therefore, to speed up processing time, all samples in the dataset were resized to 28 x 28 pixels.

**Proposed Model: -**

**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 downsample 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.

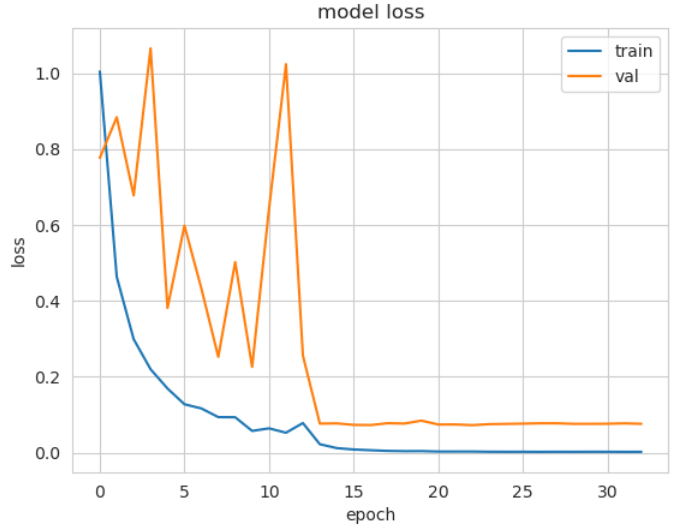
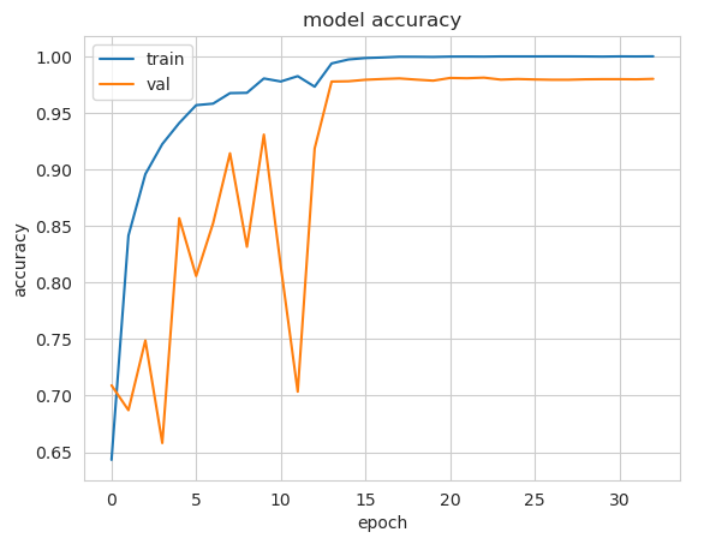
**TRNet:** The TRNet model consists of three convolution layers and four dense layers, which include an input layer, three hidden layers, and a final output layer. The model takes an RGB input image of size 28×28 and performs the convolution operation on the first three layers. In each of these layers, 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.

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| --- | --- | --- |
| **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 |

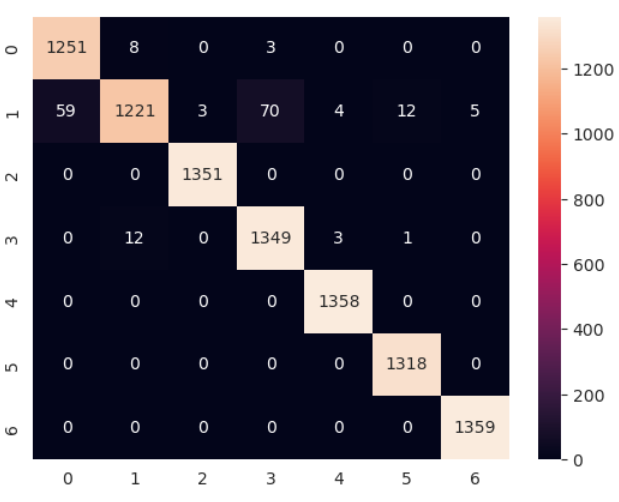
|  |  |
| --- | --- |
| **Parameters** | **Value** |
| Batch Size | 64 |
| Number of Epochs | 50 (21/50 Due to Early stopping) |
| Number of Iterations | 470 |
| Optimizer | Adam |
| Learning Rate | 0.001 to 1.0E(-8) |

**Results:** TRNet Model Test Result , Test Loss: **0.07440** , Test Accuracy: **98.08%**

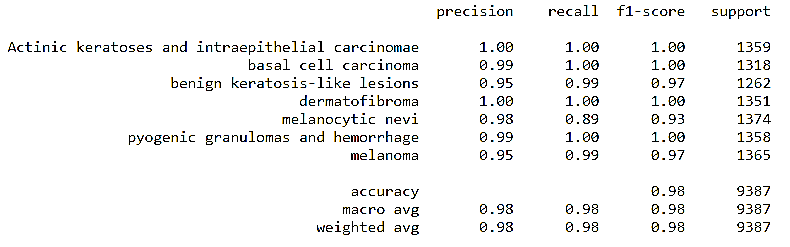
**Accuracy and Loss Graph:**

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**Correlation Metrics:**

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**Class Wise Results:**

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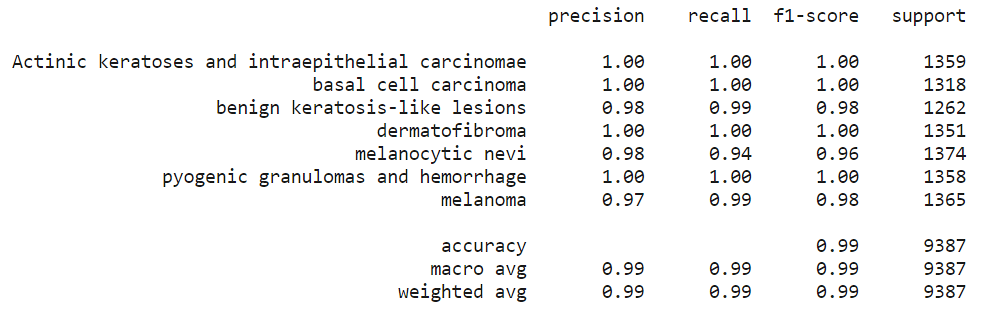
**Hybrid TRNet:** Hybrid TRNet is a novel approach that combines the TRNet algorithm with machine learning techniques such as Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression. The aim of this hybrid approach is to improve the accuracy of the TRNet algorithm 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.

**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.

**TRNet With SVM:**

**Results:** 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.

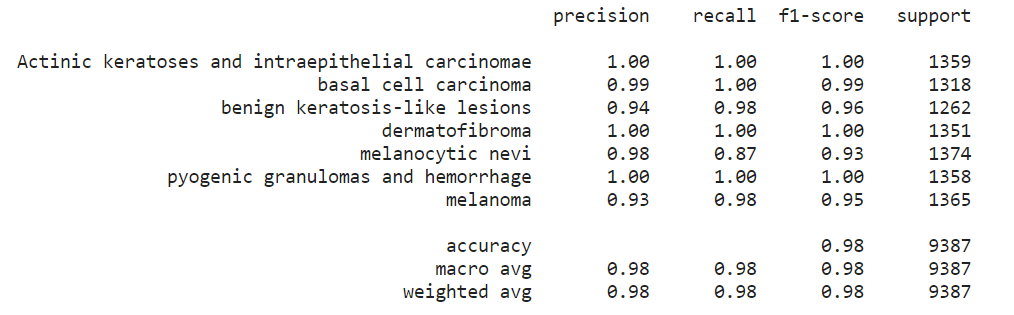
**Class wise Results: **

**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.

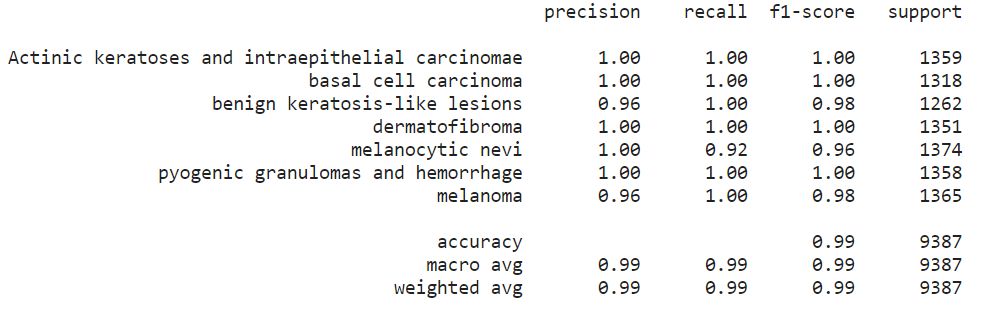
**Class wise Results:**



**TRNet with KNN:**

**Results:** Random Forest Classifier 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.

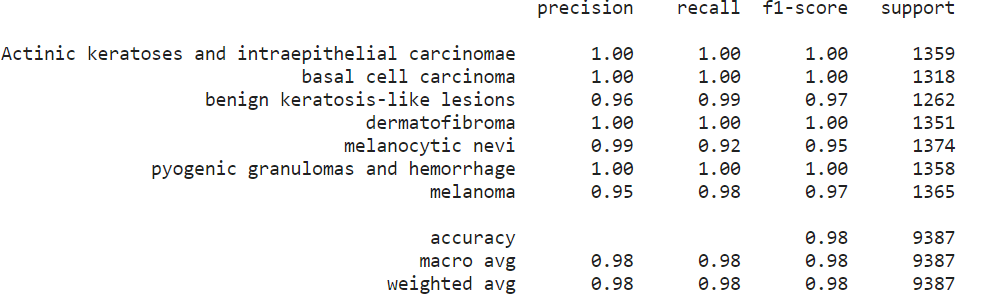
**Class wise Results:** ****

**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:**

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**Accuracy:**

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

**Abstract:**

**The application of deep learning methods in medical research has emerged as a promising approach for disease diagnosis. Among the various medical conditions, skin diseases are prevalent worldwide and pose significant challenges to healthcare systems. Delayed diagnosis of skin diseases can have detrimental effects on patients' health, quality of life, and healthcare costs. In this study, we propose TRNet, a novel lightweight hybrid learning approach for skin cancer disease image classification.**

**The proposed TRNet model leverages convolutional neural networks (CNNs) and incorporates machine learning models such as Support Vector Machines (SVM), Random Forests, K-Nearest Neighbors (KNN), and Logistic Regression. TRNet is designed to be a lightweight model, suitable for deployment on resource-constrained devices and computer systems. It offers competitive performance compared to well-known models like ResNet, DenseNet, AlexNet, and VGG16, achieving an accuracy of 98.08%.**

**To enhance the model's performance, we employ various techniques in this research. Data balancing techniques are applied to address class imbalances in the Hamm 10000 dataset, which consists of seven classes including actinic keratoses, benign keratosis, melanocytic nevi, basal cell carcinoma, dermatofibroma, melanoma, and vascular skin lesions. Additionally, we utilize Grid Search Cross-Validation (CV) optimization and K-fold validation techniques to fine-tune and evaluate the proposed model.**

**Furthermore, we evaluate the robustness of TRNet using an adversarial test dataset, demonstrating its resilience against potential attacks. The results showcase the effectiveness of TRNet, achieving accuracy rates of 98.87%, 96.65%, 99.12%, and 98.42% when combined with SVM, Random Forests, KNN, and Logistic Regression, respectively.**

**The findings of this research contribute to the field of medical image classification, specifically in the diagnosis of skin cancer diseases. TRNet's lightweight architecture, coupled with its hybrid learning approach, demonstrates its potential for accurate and efficient disease classification. The proposed model holds promise for implementation in healthcare systems, assisting medical professionals in timely and accurate diagnoses, ultimately improving patient outcomes.**

Deep learning methods have shown promise in medical research, particularly for disease diagnosis. Skin diseases are prevalent worldwide and present significant challenges to healthcare systems. In this study, we propose TRNet, a 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 is designed to be deployed on resource-constrained devices and computer systems. We evaluate the model's performance on the Hamm10000 dataset, which consists of seven skin cancer classes: melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), benign keratosis (BKL), dermatofibroma (DF), vascular lesion (VASC), and squamous cell carcinoma (SCC). The results demonstrate the potential of TRNet in accurately classifying skin diseases and addressing the challenges in healthcare systems.

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 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 achieves an impressive overall accuracy of 98.08% in skin cancer disease image classification. Furthermore, when combined with SVM, Random Forests, KNN, and Logistic Regression, TRNet exhibits even higher accuracy rates of 98.87%, 96.65%, 99.12%, and 98.42%, respectively. These results demonstrate the effectiveness and versatility of TRNet in achieving accurate classification results.

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.

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. 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:

1. 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.
2. 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.
3. 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.
4. 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.
5. 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 and malignant ones.
6. 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.

References:

1. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.
2. Brinker, T. J., Hekler, A., Enk, A. H., Klode, J., Hauschild, A., Berking, C., Schilling, B., ... & von Kalle, C. (2019). Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images. European Journal of Cancer, 123, 79-87.
3. Tschandl, P., Codella, N., Akay, B. N., Argenziano, G., Braun, R. P., Cabo, H., ... & Kittler, H. (2018). Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international, diagnostic study. The Lancet Oncology, 19(7), 937-948.

explain the role of Artificial intelligence , machine Learning , deep learning computer vision in disease detection in the medical filed

ChatGPT

Artificial intelligence (AI), machine learning (ML), deep learning, and computer vision play significant roles in disease detection in the medical field. Here's an explanation of their roles:

1. Artificial Intelligence (AI): AI refers to the development of intelligent systems that can perform tasks that typically require human intelligence. In disease detection, AI algorithms are used to analyze medical data, such as images, patient records, and genetic information, to identify patterns, make predictions, and support decision-making processes.
2. 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.
3. Deep Learning: Deep learning is a subfield of ML 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.
4. 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 disease progression, and personalizing treatment plans.

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