A MAJOR PROJECT II REPORT

ON

SKIN CANCER DETECTION USING KNOWLEDGE DISTILLATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

MASTER OF TECHNOLOGY

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CANDIDATE'S DECLARATION

I **Deeksha Jaiswal** hereby certify that the work which is presented in the thesis entitled **"Skin cancer detection using Knowledge Distillation"** in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Computer Science and Engineering, submitted in the Department of **Computer Science and Engineering**, Delhi Technology University is an authentic record of my own carried out during the period from **January 2024 to May 2024**, under the supervision of **Dr. Rajni Jindal.**

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE BY THE SUPERVISOR(s)

Certified the **Deeksha Jaiswal ( )** has carried out their research work presented in this thesis entitled **"Skin Cancer Detection using Knowledge Distillation"** for the award of the Degree of **Master of Technology in Computer Science and Engineering**, from Department of **Computer Science and Engineering**, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not for the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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ABSTRACT

Skin cancer is one of the most lethal forms of cancer, this is because it is among the cancers that are known to be invasive and can easily spread if early treatment is not sought. Photodermatitis worsens the erythema that occurs due to exposure to light and also enhances the rate at which skin cells divide. Therefore, the need to design a technique that will automate the diagnosis of skin lesion is essential for facilitation of diagnosis thus saving on time and lives.

This research suggests the development of a skin cancer classification system that is automatic in nature and is aimed to differentiate seven types of skin cancer with melanocytic nevus and angioma. The implementation uses what is known as Knowledge Distillation, a method that aspires to enhance the current form of detection by transferring knowledge from a big and complicated model (technically termed as 'teacher') to a new model that is much simpler and effective, or what is famously referred to as 'student'. The dataset comprises images of nine different skin conditions: Actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma of the skin, new, seborrheic keratosis, squamous cell carcinoma, and vascular lesion.

The proposed method works; the feature extraction and classification of Knowledge Distillation ensure that it delivers reasonably good results. These findings show that the implementation of CNN-based automated systems for image analysis in the diagnosis of skin cancer enables physicians to diagnose the cancer in its preliminary stages from medical images, which leads to higher rates of patient survival and higher effectiveness of usable treatment techniques.

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LIST OF PUBLICATIONS

1. Deeksha Jaiswal "Advancements in skin cancer detection: A Comprehensive review" Accepted at the "**International Conference on Artificial Intelligence, Machine Learning and Big Data Engineering (ICAIMLBDE)**" at Gurugram, India

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2. Deeksha Jaiswal "Convolutional Neural Networks to Automate Skin Cancer Detection", Accepted at "**International Conference on Intelligent Computing and Communication Techniques at JNU**" at New Delhi, India

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

- SCC - Squamous Cell Carcinomas
- SC - Skin Cancer
- CAD - Computer-Assisted Diagnosis
- ANN - Artificial Neural Networks
- CNN - Convolutional neural networks
- GAN - Generative Adversarial Networks
- ISIC - International Skin Imaging Collaboration
- OS - Operating System
- ML - Machine Learning
- DS - Data Science
- GAN - Generative Adversarial Networks
- SVM - Support Vector Machines
- KNN - K- nearest Neighbor

CHAPTER 1

INTRODUCTION

Skin cancer identification at an early stage is critical for a variety of reasons. First, skin cancers, particularly SCC, may develop quickly, making early detection critical to avoiding future difficulties. SCC metastases can be avoided with early identification, emphasizing the necessity of identifying the illness early. Regular skin checks beginning at the age of 18 are suggested to increase the possibility of early discovery, since early care can considerably improve five-year survival rates as well as lead in a 99 percent chance of survival when cancer is found before it spreads to lymph nodes. Furthermore, early detection is crucial for melanomas that as Stage 1 melanoma is often safe and can be cured with surgery, emphasizing the relevance. Furthermore, early diagnosis is critical since it enables the early detection of not cancerous moles, which are occasionally mistaken for malignant growths, reducing undue stress and treatments. Identifying SC in its earliest phases helps avoid superficial skin cancer from developing to life-threatening forms, highlighting the necessity of regular skin self-checks for every person, irrespective of skin tone or risk factors. In 2012, the global cancer count reported fourteen million additional cases and two million deaths, making cancer one of the leading causes of mortality. Carcinoma, a frequent kind of cancer, typically develops on sun-exposed skin areas, although it may impact any body part. It usually starts in the most apparent part of the epidermis. As a result, a CAD technology may make an initial diagnosis simply based on photographs of skin lesions. Recent research done at Stanford University found that a strong deep CNN outperformed dermatologists in terms of effectiveness. Nonetheless, its usefulness in addressing other skin diseases is unknown. Just publicly available datasets were utilized for CNN validation, training, and evaluation. The experimental design is identical as that used in the Stanford study, and comparable images are utilized wherever possible. However, certain datasets utilized during the Stanford research were unavailable, requiring the incorporation of new datasets to supplement the image pool for the disorders examined in this analysis. CNNs are highly specialized neural network designs that excel in image identification and classification. Their superiority over humans in identifying individuals, things, and roadways has resulted in their use in a wide range of applications. Researchers examined a variety of simulations, including the EfficientNetV2S and Swin-Transformer designs, to create huge combinations models in SC diagnosis. This method takes use of the properties of several models while guaranteeing interpretability, hence increasing the overall performance of automated SC detection equipment. Compared to most prior techniques SC diagnosis, that rely on a single CNN model, deep ensemble models increase diagnostic robustness and reliability. Also, the utilization of extensive methods of image processing that have been incorporated in a way that is a combination of the above methods has helped in enhancing the degree of accuracy of datasets that are used in identifying skin cancer. Using the same algorithms, highly trained practitioners have been outperformed in cancer detection, thus the application and relevance in this line. The following is a comprehensive analysis of SC detection employing Knowledge Distillation technique for the purpose of this study.

1.1 Objective:

The particular study aims at developing an advanced approach for the classification of a variety of skin cancers with the help of a detailed database provided by the ISIC. After the test on the effectiveness of the CNN Hinton-based model, the results indicate that the model has a very high accuracy rate of 79.86%. From this high figure, one can see that the model has a good reliability of the recognition of skin cancer lesion. It focuses on how one can apply more serious and complex machine learning methods to dermatology in order to improve diagnostics and arrive at the correct diagnosis of skin cancer sooner. There is promise in this research for the improved effectiveness of patients' treatments, as well as the process of diagnostics in healthcare systems. Therefore, we tried to implement knowledge distillation technique to build this model.

1.2 Problem Statement:

Firstly, the main objective is to explore how well the model discriminates skin cancer lesions. As a result, this project demonstrates how Knowledge Distillation-based models can be beneficial in dermatological diagnostics and create a reliable automated system for initial skin cancer decision. Perhaps the last objective is to contribute to the development of complex diagnostic capabilities that would improve patients' lives, support clinicians to work more efficiently, and address the burden placed on healthcare organizations.

1.3 Software Requirements:

1.3.1 Operating System

- Windows (version 10 or later): is an Open Operating System which can run a variety of applications and computer programs and sustain application development platforms.

- Linux (Ubuntu 18.04 or later): which is more reliable, secure, and provides better support for execution and development of machine learning applications and tools.
- macOS (Version 10.15 or later): A stable and flexible OS well liked among developers as it is built on the UNIX environment and is easy to integrate with other Apple products.

1.3.2 Development Environment

- Integrated Development Environment (IDE): Editors like VS Code, PyCharm, and Jupyter notebooks offer ample access to the coding, debugging, and administration opportunities.
- Programming Languages: Python 3.7 or later were chosen because of simplicity of code and syntax, existence of many libraries in general, strong community support for any upcoming problem in this language in particular for ML & DS.

1.3.3 Libraries and Frameworks

- Deep Learning Frameworks: TensorFlow 2.x, Keras as well as PyTorch are already existing platforms employed in constructing as well as training neural networks.
- Image Processing Libraries: This comes in handy when you are likely to use common open-source tools such as OpenCV or scikit-image that are useful for reading, manipulating or pre-processing image data.
- Data Handling: While processing the data, mathematical operations such as calculations and data transformations are accomplished by using NumPy and pandas.
- Visualization Tools: Matplotlib and seaborn are utilities for creating more complex and intricate plots and charts to analyze collations and patterns of data and models.

1.3.4 Database Management

- By using MySQL, PostgreSQL, or MongoDB/database and related data and additional information which are image, it is safe and effective.

1.4 Hardware Requirements

1.4.1 Processor

- CPU: For general development and the first training of the initially trained model, use the Intel Core i7 processor or the AMD Ryzen 7 processor with similar performance.
- GPU: It is possible to employ NVIDIA GPUs with CUDA (for instance, NVIDIA GeForce GTX 1080, RTX 2080, or later) to improve the efficiency of training the deep learning model and significantly reduce the computing time.

1.4.2 Memory

- RAM: For efficient data processing and also for scaling deep learning models and its applications, it is recommended to have at least 16 GB (preferably 32 GB).

1.4.3 Storage

- Hard Drive: Ssds for the storage of massive image databases, and any other requisite files, if in size of at least 1 TB.

1.4.4 Graphics Processing Unit (GPU)

- Dedicated GPU: Deep learning parallel calculations require a GPU supporting CUDA such as NVIDIA Tesla V100 or RTX 3080 and newer.
- GPU Memory: For training the big models of neural networks in training, and for data handling a minimum of 8 GB VRAM is required, but 16 GB VRAM or more is recommended.

1.4.5 Peripherals

- Monitor: New monitors enable high resolutions or pictures and visualizations to be shown in great detail, helpful for diagnostics and review.
- Keyboard and Mouse: Standard input devices are enhancements for swift coding and long-screen control.
- External Storage: For backing up dataset and model files, its universal use is portable hard drives or cloud-storage for security and for sharing.

1.4.6 Network

- Internet Connection: There is a continuous need for a fast and reliable internet connection to download datasets and libraries and get access to the tools, remote work, and deployment.

CHAPTER 2

FEASIBILITY STUDY

Feasibility analysis can be defined as a study that aims at establishing the likelihood of success of the intended business venture or an initiative that is intended to be undertaken within a business organization. I also feel that it investigates a lot of avenues before establishing if such a notion is possible and feasible. This coming analysis is meant for the purpose of assessing the risks and factors that might hinder the progress and, in the process, predicting the possible outcome to ensure the compatibility of strategy and resource. A feasibility study consists of the following important components: Some of the important details that compose feasibility study include:

2.1 Technical Feasibility

Assessment of Technology

- Utilizing reliable and well-supported deep learning frameworks including TensorFlow or PyTorch and image processing libraries like OpenCV, the project fully enables the construction of a CNN-based skin cancer detection system.

Technical Resources

- Technical experience which should be possessed by a proper candidate includes proficiency in Python and other programming languages used in the model, knowledge on the machine and deep learning and image processing. The required infrastructure contains high-performance GPUs for training models which are present and affordable.

2.2 Economic Feasibility

Cost-Benefit Analysis

- They include cost association with purchasing systems that can perform complex computations or data acquisition costs as well as costs related to developing the models. Maintenance costs can be seen as a current expenditure because they are regular and necessary throughout the exploitation of the Software; Update expenses are also recurrent and a part of the Software's regular functioning; lastly, the Cloud Storage fees may be a substantial expense that has to be considered in relation to the Software's current cash expenditures. The expected benefits include increased effectiveness concerning diagnosis, dermatologists' time, and possibly, healthcare expenses, due to previously undiagnosed diseases.

Budgetary Considerations

- The hardware expenses involve GPUs and storage media for the project while the software costs may include premium versions of some of the tools that will be used in the project Fluorescence microscopy was done by hiring data scientists and developers for the project. The organization needs to make sure it has adequate funds available so that funding these costs are not an issue throughout the software development project's lifecycle.

2.3 Legal Feasibility

Regulatory Compliance

- It must meet the qualifications of the sector to which it belongs, for example, patient data should be protected under the HIPAA policy if the project is in the States or the GDPR policy if the patient is a citizen of the EU. It is always important to remove identifiers from the dataset and use it in the right manner to avoid bias.

Legal Risks

- Some of the legal concerns which are associated with this type of use are data privacy break-ins, medical data misuse, and matters to do with Intellectual property rights. There are precautions to be taken with it such as strong security measures, source data acquisition through legal means, and adherence to all of the laws that exist regarding such practices.

2.4 Operational Feasibility

Process Assessment

- Adapting the use for the automated detection system in today’s practices of dermatology should help to cut down on the workload. The system should be easy to use so that a health care provider does not need to spend a lot of time training themselves to use it, and it has to be easily integrated with EHR systems, if any, available in the health care setting.

Human Resources

- The project must have workforce with adequate skills such as in machine learning engineers, software engineers, and advisors with medical background. The human resources such as professionals working in the organization for human resources must be available so that they can be reverted back to the project.

2.5 Schedule Feasibility

Timeline Analysis

- There is a likelihood that the process of developing and deploying this particular system will take several months, in the course of undertaking activities such as data acquisition and preparation of data, training and fine-tuning the model, as well as testing the system prior to its implementation. The goals for the project need to be realistic and require appropriate time because early times could lead to unrealistic expectations.

Project Milestones

- Successful completion of the data set creation process, initial model creation, and validation of the model as well as the beta version for the users is the major accomplishment for this period. These are very important in that they provide check points that help control the progress and to ensure that efforts are focused on key activities.

2.6 Market Feasibility

Market Demand

- One can note the growing importance of using automatic diagnostic support in healthcare, especially since diagnostic tools are required to be faster and more precise, given the further spread of skin diseases. Considering the target audience, the system meets a growing demand by offering an effective and credible way to detect the disease in the initial stages.

Competitive Analysis

- This means that the competitors are the other diagnostics carried out by the use of AI, including computer diagnostic tools and the general diagnosis methods. The proposed system can have a competitive edge compared to other practices and models in terms of-classifying not only one, but several forms of skin cancers accurately without necessarily having to be integrated into the computer-Aided Diagnosis systems, thus could act as an add-on system to enhance other systems.

CHAPTER 3

LITERATURE SURVEY

Skin cancer is among the most common types of cancer and it is very important to diagnose such malignancy at an early stage in order to have the best prognosis and chance to cure the disease. Due to the progress in machine learning and image processing methods, skin cancer diagnosis has improved over the recent past by offering accurate and efficient diagnosis tools. This literature survey provides a brief outline of major research papers and advances in the area of application of skin cancer detection using automated methods.

Below are research concerning the methods on how one can find gaps and research on skin cancer detection.

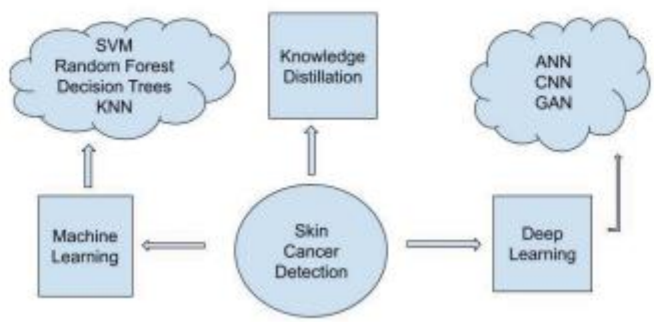


Fig 1. Methods discussed to study Skin Cancer Detection

3.1 Study of Various methods in Skin Cancer Detection

3.1.1 Traditional Methods

In this study we are discussing the three major conventional diagnostic techniques of skin cancer that includes visual examination, dermoscopy and biopsy. Dermoscopy improves skin brightness and contrast enabling detection of deeper and clinically undifferentiated melanomas. However, these methods are not very scientific and analytical and they solely depend on the qualifications of the clinician performing them.

3.1.1.1 Dermatologist Examination

- In this method of diagnosing skin cancer, dermatologists rely on their eyesight to recognize the cancerous skin.
- This group of practitioners is capable of recognizing the different forms of skin cancer.

3.1.1.2 Dermoscopy

- Improves diagnostic yield and sensitivity in melanocytic neoplasms, basal cell carcinoma, and squamous cell carcinoma that its overall accuracy rate is 89% [1].
- Issues are present, especially with lesions in their early stages containing features that cannot be distinguished easily from Dermoscopy [1].

3.1.1.3 High-Tech Imaging Devices

- Total body scanners can measure the patient's biometrics and progress with tremendous accuracy which will be useful in conditions that require constant checking and adjustment of the patient [2].

3.1.1.4 Biopsies

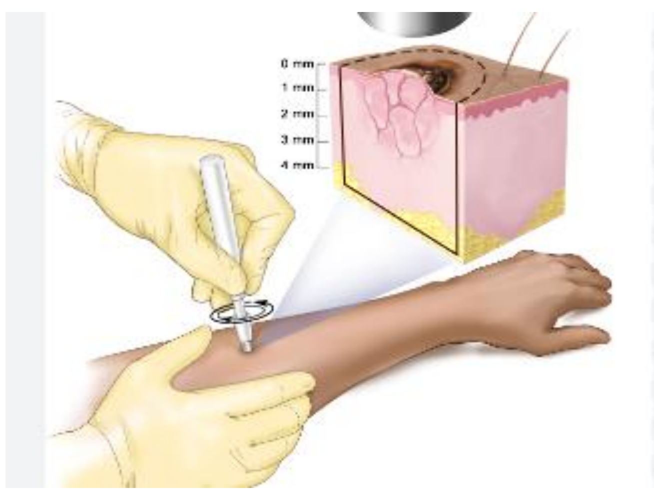


Fig 2. Biopsy Procedure

- Procedure: This is involves taking a small sample of tissue from the suspicious lesion in order that pathologist may have a look at it under the microscope.
- Types:
  - Shave Biopsies: A procedure that peels off the highest layers of skin, utilized in treating different forms of minor skin changes.
  - Punch Biopsies: Employ a cylindrical sort of gadget to get samples of deeper tissue superior.
  - Excisional Biopsies: complete excision of the lesion along with a margin of normal skin is as important in the treatment of NM as it is in other types of skin cancer.
- Advantages: Diagnoses specific types of cells, indicates present cancer type and its malignancy, and assists with the selection of further therapy.
- Limitations: It is invasive in nature; it may cause mild pain and leave scars behind; it is not very effective in all cases especially in the case of atypical skin tissues [3].

3.1.1.5 Genomic Testing

- Procedure: Examines the deoxyribonucleic acid or ribonucleic acid of skin cells to search for the gene alterations that cause skin cancer.
- Advantages: Improves the accuracy of diagnosing skin cancer and vice versa.
- Challenges: Some of these limitations include: Likelihood of misinterpreting complex genetic variants, lack of standard operating procedures in handling, collecting and storing specimens, patient's privacy and the consent issues [2].

3.1.1.6 Self-Examination and Clinical Examination

- Visual Self-Exams: Yearly full-body examinations by skin doctors, and monthly skin self-examinations [4][3][4].
  - Methods:
    - ABCD Rule: Asymmetry, Border irregularity, Color variation, Diameter (>6mm) [6].

- Seven-Point Checklist: Asymmetry, border irregularity, color variegation, diameter >6mm, evolution/change in size, sensation (itching/pain), bleeding [6].
- Menzies Method: Asymmetry: measures how balanced the circles are around the edges of the pattern; Border irregularity: measures how smooth the edges are of the circles; Color variegation: measures the distribution of the colors in the pattern; Structural features: measures the ph feature of the pattern according to [6].
- Pattern Analysis: It helps in the differentiation of malignant and benign lesions [6].

- Clinical Examination: Doctors inspect lesions, which may be papules, plaques, nodules, vesicles, or bullae, commenting on their dimensions, pigmentation, surface configuration, and whether they hemorrhage or scale.
  - Lymph Node Examination: Checks nearby lymph nodes for enlargement if cancer is suspected [3].

3.1.2 Machine Learning: Deep learning as a subset of machine learning has been found to be useful in the detection of skin cancer, through feeding skin lesion dermoscopic images to develop models on a large dataset with the ability to categorize different types of skin lesions.

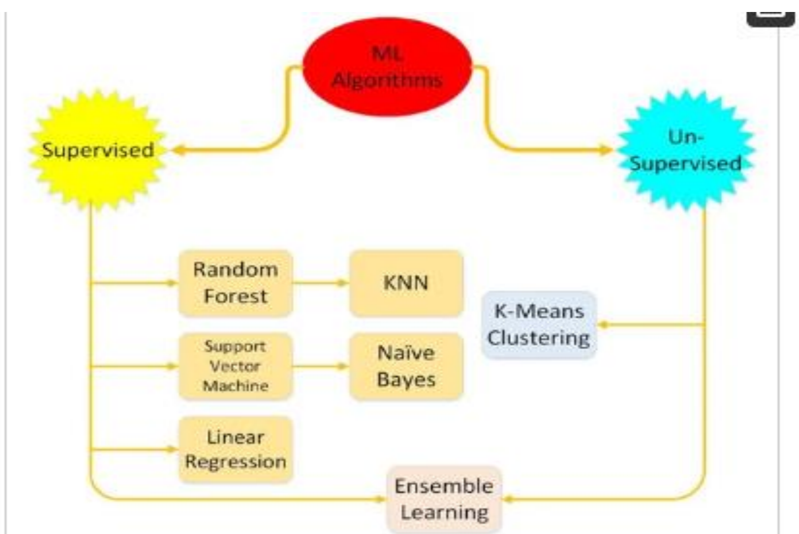


Fig 3 Machine Learning Algorithms structure

Machine Learning algorithms discussed here:

3.1.2.1 Random Forests

- It proved helpful in the classification of skin lesion and the identification of the areas having cancerous growth [5].
- Determine the proportion to be assigned for each sample and use decision points that are relative to the Gini index.
- This also provides a sound approach of going about analyzing complicated data sets.
- Previous research has demonstrated different high degrees of accuracy in classifying the dermatoscopic images into narrower subtypes thus aiding skin cancer detection [7].

3.1.2.2 Segmentation Techniques

- Thus, by applying the concept of thresholding, attain excellent, first-class rates of accuracy of prediction, which may hover around 97.4% [6].
- Previse becomes useful in differentiating malignant tissues from normal surrounding tissues of the body.

3.1.2.3 K-Nearest Neighbors (KNN)

- It has achieved very high accuracies when integrated with the firefly algorithm for the classification of skin lesions [8].
- These are recall and precision rates that suggest the subject approach works effectively for predicting possible regions with cancer.

3.1.2.4 Support Vector Machines (SVMs)

- Helpful in detecting infections and carcinoma in its early stage the remarkable role [9].
- They achieve high classification rates when the ABCD method is combined with SVMs especially for melanoma, seborrheic keratosis and lupus erythematosus.

- Discover those hyperplanes that exist between different categories of skin lesion and present a strong regularized learning model to well segment cancerous and non-cancerous areas from the lesions.

3.1.2.5 Fuzzy K-Means Clustering

- Useful for identifying pertinent regions of interest in preprocessed clinical images [10].
- It assists in the process of recognizing melanoma later on by separating skin lesions and reducing spread of variation in objects in each set.

3.1.2.6 Decision Tree Algorithms

- Have magnanimous contributions towards the image pre-processing and classification, reflecting higher levels of accuracy [11].
- Applying median filters for the purpose of reducing the noise in the image and histogram equalization to improve the contrast of the image.
- There remain challenges in skin cancer detection, for instance, feature extraction techniques such as area, mean, variance and standard deviation improves the strength and reliability of Decision Tree Classifiers.

3.1.3 Deep Learning

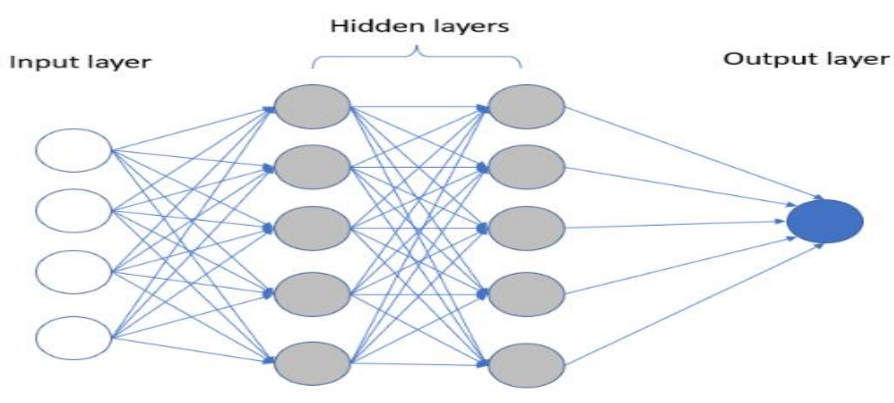


Fig 4. Basic Structure of deep neural network

3.1.3.1 Artificial Neural Networks (ANNs): Although ANN’s are considered formidable in skin cancer detection and classification, significant improvements in diagnostics are observed when using various methods.

- The work done by [12] in his study use a model known as the Artificial Neural Networks (ANNs) to distinguish between cancerous skin lesions and benign ones. Despite the mentioned limitations, applying segmentation and feature extraction helped the study to get a total accuracy of 0.97 or 97 percent. 4%. This demonstrates the ability of the chosen ANNs to properly classify skin lesion according to their malignancy levels.
- In [13], the authors used some high-level preprocessing methods on the input images; the next, the application of the segmentation stage, and feature extraction stage that helped the process of classification. The study used feed-forward neural networks with backpropagation to classify skin lesion by identifying the learned characteristics. This approach seek to elaborate on how ANNs can be useful in enhancing the odds of diagnostic precision in skin cancer.
- The work by [14] was focused on the design of efficient but affordable tele-support systems for processing the medical images, using the ANNs with the BPA to design the digital diagnostic algorithms. This approach achieved a high accuracy of 96 percent in the classification of vitality images taken by the Vitamaster device. 9% in identifying skin cancer thereby boosting up the overall functionality of emergency medical treatment.
- The work done by [15] applied ANNs with preprocessing, extraction of features, and classification in skin cancer detection. In this way, the study was trained with the SCALED CONJUGATE GRADIENT (SCG) ALGORITHM and obtained an accuracy of 84. 21% proving that ANNs work in this context Even the general recognition rate is fairly high, reaching The level of general recognition is rather high, 21% .
- [16] successfully used binary thresholding for the segmentation of skin lesions, followed by feature extraction and training of the neural network for the detection of skin cancer. The success rate of this method is 97 percent which means that the long term storage of data using this method is very effective. Specificity was at 84% in the precise classification of the lesions, and these findings give credence to this composite system.

3.1.3.2 Convolutional Neural Networks (CNNs)

- This work proposed by [18] has introduced an artificial system that integrated image processing and machine learning features. In a related note, while scoring an accuracy of 89 the automated tool made a considerable improvement in comparison to the manual input. 5%, it is stipulated how important it is to have good performance across different datasets and different real conditions. This goes to show that there is need for much more improvement in order to optimize the operation of the system to varying terrains.
- The study conducted by [19] focused on the usage of the Convolutional Neural Network (CNN) algorithms with intentions of distinguishing between skin lesions that are benign and those that are malignant. The testing of the developed model, the VGG-16 achieved a classification accuracy of 87%. 6%. The importance of a range of generalization across all categories of patient and skin types was further underlined and it indicated the need to expand such research for applicability to as many distinct patient populations as possible.
- [17] conducted a study where they proposed a deep learning-based framework, specifically Convolutional Neural Network (CNN) based for the purpose of skin cancer lesion detection. Nonetheless, published results that form the basis of clinical decision support application have some limitations that require improvements in terms of scalability and computational complexity in large-scale clinical practice settings.
- Analyzing the research of [20], they aimed at comparing the outcomes of Convolutional Neural Networks (CNNs) for skin lesion classification through a systematic review. They discussed obstacles related to drawling references for various architectures and datasets and stress the need for establishing common framework and generally available datasets to provide solid grounds for comparisons and development progress.
- Worthy works of [21] and [22] demonstrated the prominent accuracy and efficiency while classification of skin lesions through new Convolutional Neural Network (CNN) approaches. These studies underpinned the potentiality of deploying CNNs in conjunction with technologies including NLP and optimization techniques to enhance the accuracy of the diagnosis and the efficiency of the practice patterns.

3.1.3.3 Generative Adversarial Networks (GANs)

- Another study by Rashid et al. [24] utilized GANs to generate new training data since most databases used in the development of deep learning models had limited skin lesion images. Using deconvolutional network as the generator and CNN- SRN as the discriminator, the study made the accuracy of 86 percent. 1%. This highlighted the agenda of having different and well balanced datasets for various models in order to enhance the generalization of skin lesion classification models.
- Built off previous research from Bisla et al., the integration of GANs helped to augment and improve datasets to help an increased accuracy of skin lesion classifications to 86. 1%. This scholarship demonstrates the ways in which GANs can be useful in increasing datasets and the performance of models for skin lesion classification.
- Teodoro et al. [23] proposed EfficientAttentionNet for accurate diagnosis of melanoma and non-melanoma skin lesions' existence. To further improve the quality of images, they adopted a set of operations that they referred to as the preprocessing stage. They further relied on GANs to guarantee an impartial pattern distribution. In addition, specific networks were used for weeding out region boundaries within the image and this made skin lesion classification highly accurate.

3.1.3.4 Computer Vision

- As described in the study by Mengistu et al. [26], authors have also explored the possibility of using selected methods of digital image processing to include and classify skin cancer. The study also highlighted the provision of end-to-end mechanisms that are strong and easily scalable with the help of integrating complex algorithm of current machine learning. In addition, it emphasized on technological competence in real time processing for quick detection and management. The researchers also provided solutions regarding the quality of images and medical expertise that are imperative for the consequential utilization of help from computer-assisted technology in the diagnosis of skin cancer.

3.1.4 Knowledge Distillation: Knowledge distillation involves the process of converting a large complex model that requires much effort resources and time into a small light model with substantial accuracy. Based on contributions of knowledge distillation, with optimized efficiency and performance of machine learning models which makes the KM models usable in real situations such as image recognition and natural language processing.

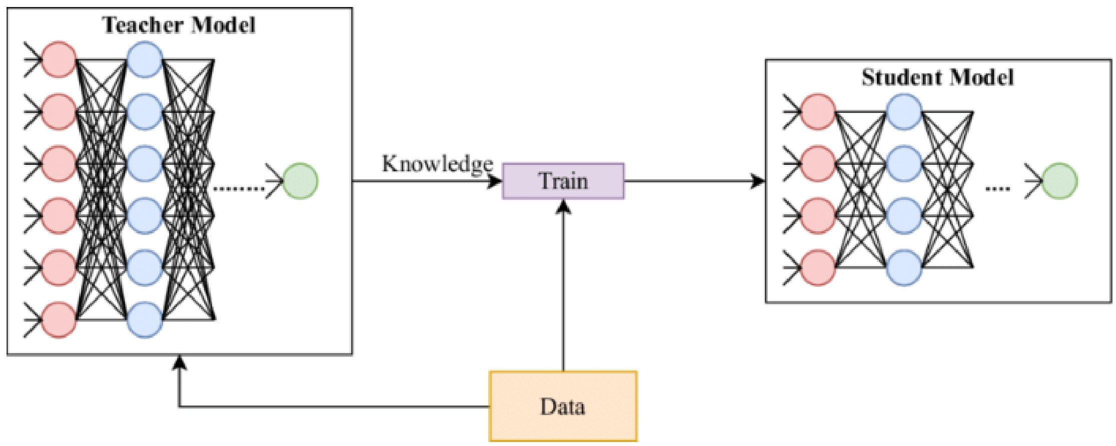


Fig 5. Structure of Knowledge Distillation

- To this end, researchers in [27] sought to employ knowledge distillation for simplifying models in detecting melanoma by leveraging dermoscopic images. To begin with, the authors pre-trained a teacher model known as ResNet-50 to classify the melanoma lesions. Beside them, they formed a Distilled Student Network (DSNet) that was comprising only 0. 26 million parameters. However, the performance of the proposed DSNet is all the more remarkable where it attained the accuracy of about 91. achieving 73.7% accuracy, surpassing bigger models as EfficientNet-B0 for both melanoma and non-melanoma skin cancers. In addition, the work of DSNet was faster during the inference phase since it only took 2 minutes for the networks to make predictions. This is 57 seconds compared to 14, When the number of symbols is greater than 22, This was observed while having more than 22 symbols; it took 57 seconds, on average, compared to 14 seconds executing if the number of symbols was less than 22. 55 seconds for larger models as such, it would be more effective to use NGT for faster translation times, such as in live translation scenarios or for larger models.
- In [28], the authors describe a way to address the problem of highly skewed data set issue to classify melanoma using a light-weighted Deep-CNN based framework. Their strategy also included improving sensitivity scores through cost-

sensitive learning and using Focal loss, as well as an in-painting algorithm used for pre-processing to remove image noise. Also, they proposed new Cut Out variants as normalizers to avoid issues of over-fitting of the model. Assessment of SIIM-ISIC Melanoma Classification Competition - Datasets of the ISIC-2020 challenge exhibited notable improvements and engaged a student model of EfficientNet-B2 that was trained using the knowledge distillation technique and revealed fantastic AUC of 0. 0.9295 as well as the sensitivity of 0. 8087.

- SD-KD was proposed in [29] as a unified framework for knowledge distillation particular for skin disease classification with the incorporation of different knowledge sources. Their method involves an intra-instance relational feature representation and the authors also proposed a dual relational knowledge distillation architecture, which are self-trained. The results of experimentation conducted with the help of the ISIC 2019 dataset revealed that the distilled MobileNetV2 could achieve the maximum accuracy of up to 85 percent in the classification of eight different disease skin types with a minor number of parameters and fewer computations.

3.2 Study of Comparisons of these Studies

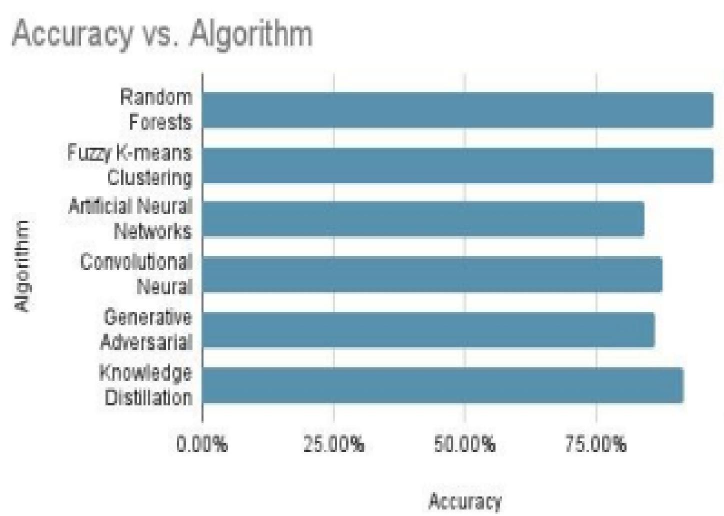


Fig 6. Graph Showing Comparison of accuracies of all the algorithms

Therefore, comparing the accuracies of a range of different learning algorithms for diagnosing skin cancer, it is possible to conclude that Random Forest and Fuzzy K-means Clustering are the winners with the result of around 97. This level of diameter size precisely encourages the construction of lesion plausibility and 4% accuracy of the proposed appearance. Here, the performance is also high, and the scores vary within the range of 87. 6% to 89. It produced a 5% accuracy rating in evaluating dermatological pictures and is a far cry from being perfected but showed a great deal of potential for automated diagnosis. DSNet specifically uses knowledge distillation which can give high accuracies of 91. 7% in addition to developing mini-models which are suitable for use in resource-limited gadgets. However, In terms of performance, Support Vector Machines and Artificial Neural Networks can be further optimized with further enhancements. Generative Adversarial Networks and EfficientAttentionNet hold the key to diagnosing skin cancer using more exotic real image processing techniques.

CHAPTER 4

METHODOLOGY

4.1 Methodology: These are the steps followed in the implementation.

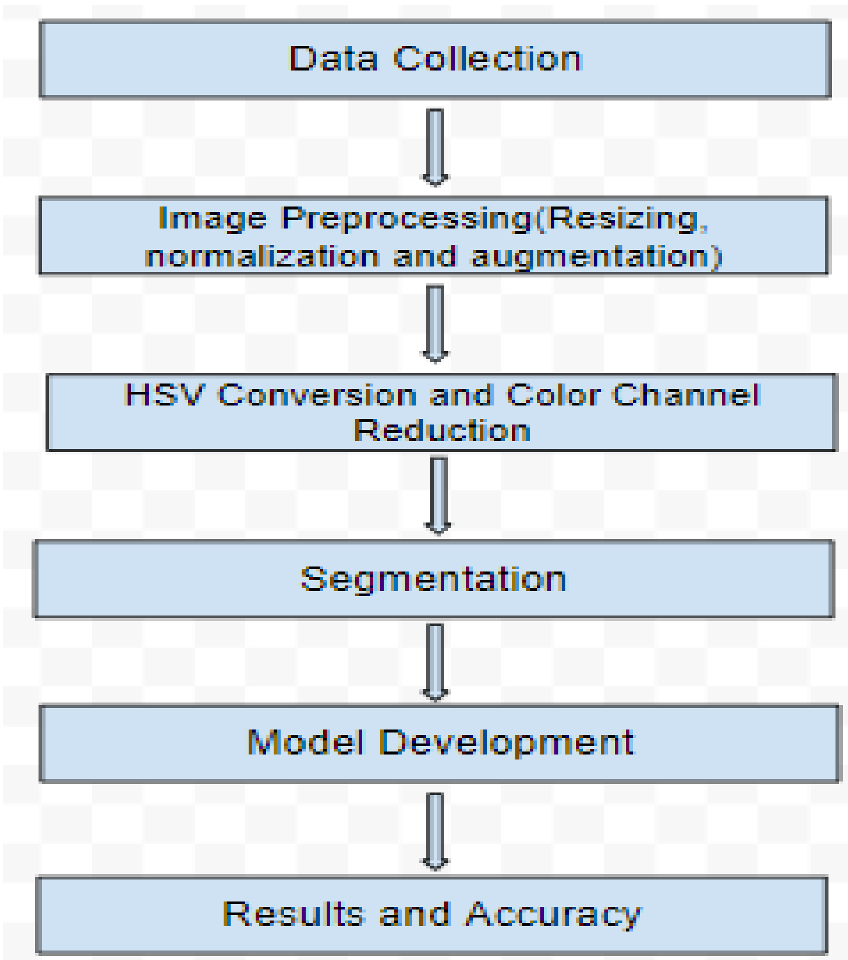


Fig 7. Process Overview

4.1.1 Data Collection:

ISIC archive is beneficial for the field of dermatology and for solving problems related to computer vision and machine learning which is the detection and identification of skin cancer automatically. This vast benchmark comprises a plethora of dermoscopic images and is divided into distinct categories of skin lesions with high grading precision. Non-symmetric skin lesions are the wide range of skin cancer that includes actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma, and vascular lesions.

The ISIC database contains detailed annotations for each picture that defines its exact location with annotations, allowing for accurate classification and optimal training of machine learning algorithms. Cohort: The images are sourced from various places; they cover various ethnicity and age making the dataset free from bias and more reliable.

One notable element of the ISIC dataset is that it contains a slightly disproportionately larger number of images of melanoma compared to other skin lesion types, which equally corresponds to the heightened clinical importance of melanoma as a predatory form of skin cancer in this area of study. However, the given dataset still provides a significant number of images for all the categories and helps to prevent the formation of an unbalanced sample and improve the training and testing of algorithms.

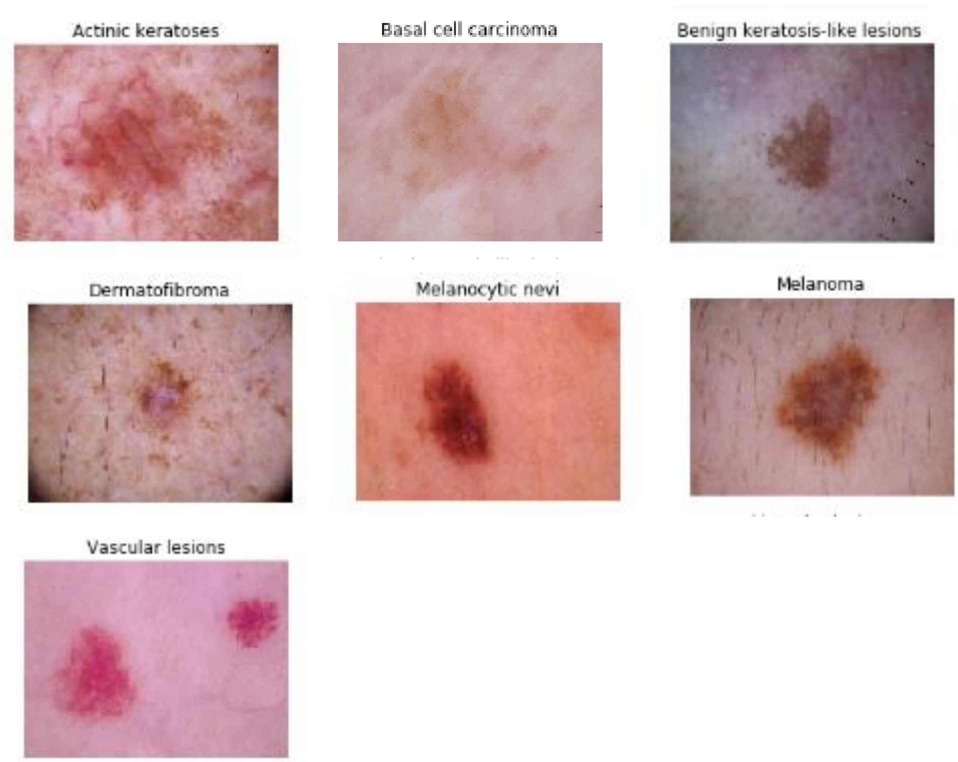


Fig 8. Dataset Images

4.1.2 Image Preprocessing (Resizing, normalization and augmentation):

Specifically, the pre-processing of images is one of the fundamental stages in data preparatory and particularly important for medical imaging analyses. It has a number of approaches that attempt to improve the quality of the images and normalize data for models for which the differences may have a bearing on the performance. First, it is required to resize the image, normalize the pixel intensity values, and eventually perform data augmentation.

4.1.2.1 Resizing: Binning on the other hand outlines entail scaling down all the images with reference to a particular size. This is important because the majority of Convolutional Neural Networks (CNNs) dictate that input samples be of a set size. When critically sizing the images, we get a uniformity of the images so that they are in harmony with the model. This helps the algorithm in handling the images in a batch without having to undergo transformation costs. For this purpose implementation of images are skewed to ensure it has a measure of equal proportions. They also resized the images to the size of 224 by 224 pixels to match the dimension required by the CNN model.

4.1.2.2 Normalization: is the scaling of each pixel value in such a way that can be easily compared with images whose normalized values of pixel range between 0 and 1 or -1 and 1. After scaling with this, the images pixel values are then normalized to a standardized scale. Values are scaled to the range of [0, 1] by normalizing with the maximum gray level possible where 256 being the maximum for an 8 bit image. This step aids in ensuring that the input data has a distribution that is somewhat similar to one of the distributions, and this helps in speeding up the convergence of the neural network at the time of training. Normalization establishes the ability to minimize the problem that may arise from different lighting conditions and object intensity which in turn help the model in determining the general pattern in the data.

4.1.2.3 Data augmentation: entails creating other samples of data by applying some operation on the available images and labeling them. Standard operations like rotation, flipping, zooming, and changing the color are often used when distinguishing between the two sets of images. Augmentation applies modifications to the dataset that enhances the training corpus so that the model can be more generalized when presented with new data. It is useful in minimizing overfitting by making the model experience diverse training scenarios in its quest to achieve higher performance.

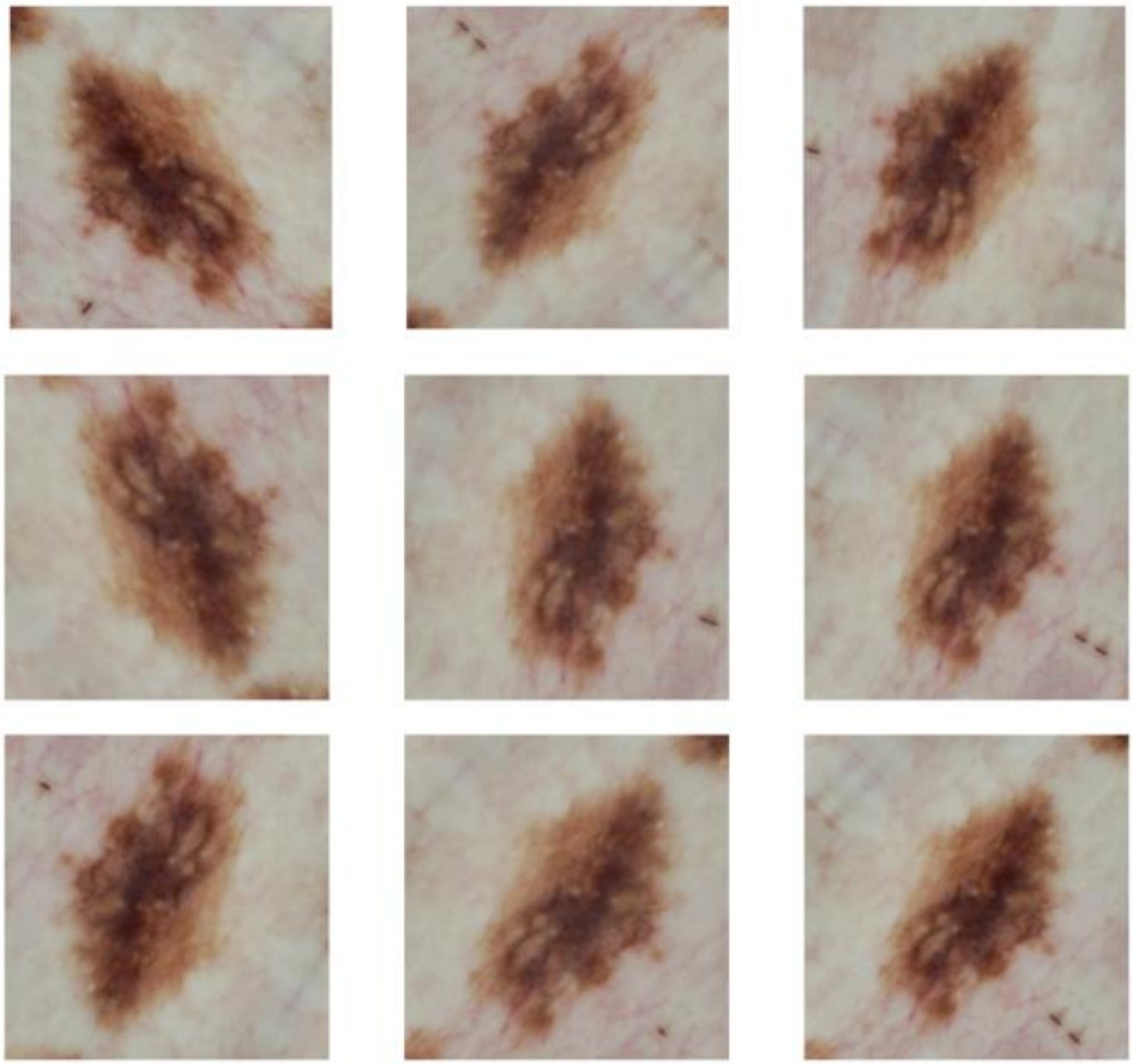


Fig 9.   Images after augmentation

4.1.3 HSV Conversion and Color channel reduction

4.1.3.1 HSV, that is an acronym for Hue, Saturation, and Value, can be used as the color space that is more ease to visualize than the traditional RGB color space which stands for Red, Green, and Blue. Converting an image from RGB to HSV is particularly beneficial in medical image analysis, including skin cancer detection: Converting an image from RGB to HSV is particularly beneficial in medical image analysis, including skin cancer detection:

- Hue is the categorization of a color being warm, cool or even a primary color like red, blue, yellow and so on. Another use that is closely related to dermatology is that different shades of color can be used to distinguish between different forms of skin changes.
- Saturation indicates how much a color is ‘spiked’ or ‘purer’. High Sat varies in the range of 0 – 255, and high Sat value means a vibrant color as opposed to low Sat value, which means near-gray color. This can help in the differentiation between skin lesion types and even help with histopathologic interpretation.
- Value shows how bright or dark the color is and helps to distinguish the feature that is lighter and more dark, correspondingly brighter or darker in comparison with the normal skin, to reveal the possible disease.

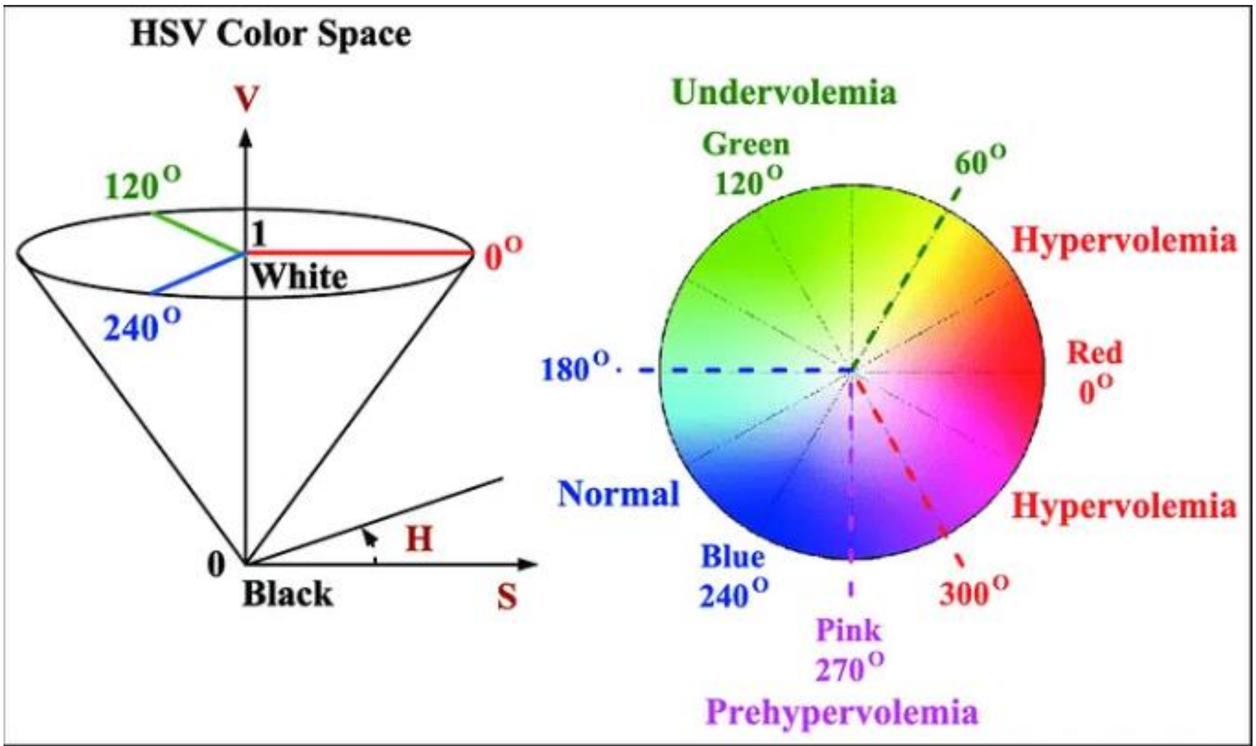


Fig 10. HSV Color Space

Data preprocessing is an important technique in which inputs are transformed so that unwanted features or noise are removed and the usefulness of the data is enhanced; in the case of images, the transformation from RGB color space to HSV color space is a good example of how this can be achieved through conversion because each of the components which make up the HSV color model can be adjusted and studied independently to increase the chances of efficient feature extraction and classification.

4.1.3.2 Color Channel Reduction

Color channel reduction involves decreasing the number of channels used in an image, simplifying the model, and reducing computational load without significant loss of critical information: Color channel reduction involves decreasing the number of channels used in an image, simplifying the model, and reducing computational load without significant loss of critical information:

- Grayscale Conversion: If the need for color differentiation is not very stringent, the image can be reduced to a single channel and turned to grayscale, reducing the load and time needed for further processing.

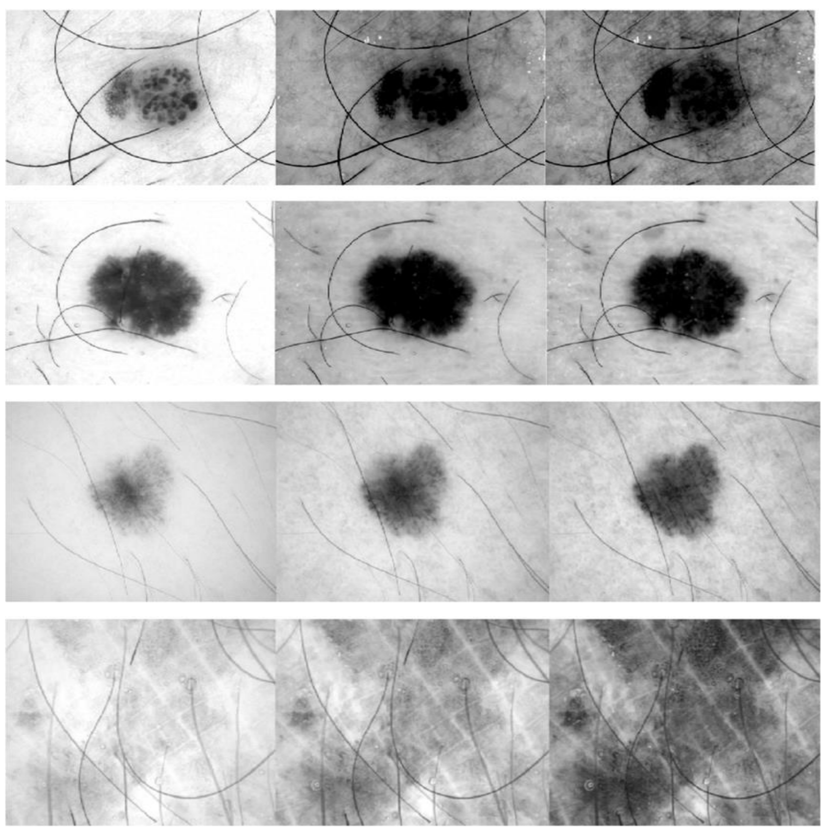


Fig 11. Skin images after grey scale conversion

Applying HSV conversion and color channel reduction as part of the preprocessing helps improve the effectiveness and reduces the direction of the pipeline. The utilization of HSV conversion enhances the color features' readability while using the channel reduction makes the data rather easy to deal with and shortens processing time.

4.1.4 Segmentation:

Image segmentation is defined as a division of an image into regions which are significantly different from each other and can be referred to as segments. The objective is it convert the current representation of the image into a new representation which is easier to understand.

It is an essential process in the context of image processing since real-world images do not always exhibit a single object of interest that a vision system needs to categorize. For example, for self-driving cars the image would have the information about the road and what cars, pedestrians, etc. are present on this road So we need here segmentation to separate objects and carry out the image classification to understand what object is.

Thresholding: This simple technique involves applying contrast so that the lesion is segmented from the background based on a threshold value. Image intensities greater than a designated partition value are assigned to the lesion and those less than this value to the background. One of the simplest methods to perform image segmentation by thresholding yet can be also completely inefficient in case of the images with low contrast or much noisy area.

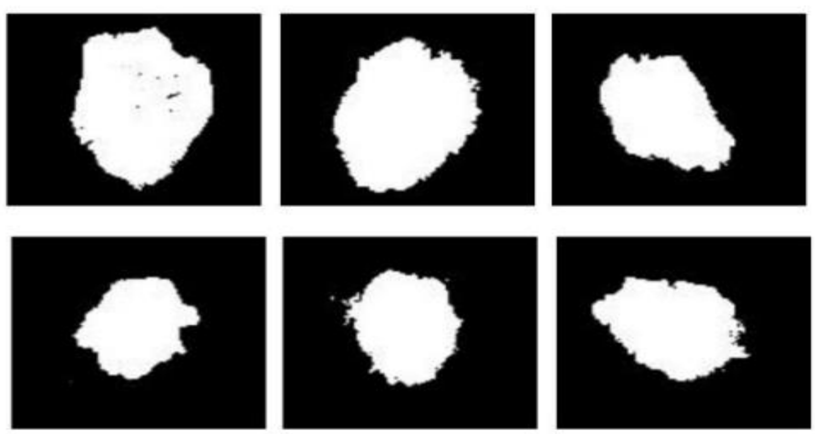


Fig 12. Images after segmentation

4.1.5 Model Building: Knowledge Distillation

4.1.5.1 **Teacher Model:** ResNet-50

The selection of the teacher model is made using the ResNet-50 model because of the higher performance and popularity of this model to solve image classification problems. The ResNet-50 is a deep convolutional neural network that incorporates residual connection which can effectively alleviate the vanishing gradient issue and thereby effectively train very deep networks.

Model Architecture:

Input Layer: Captures images of skin lesions for dermoscopy.

Convolutional Layers: In order to reduce the number of feature maps, a series of convolutional layers with ReLU activations and batch normalization were applied.

Residual Blocks: Stacked feature maps with the number of modules amounting to over eighteen, that include residual blocks in order to learn residual functions with regard to the input layer.

Fully Connected Layers: This forms dense layers that in the end produce prognosis chances of each course with regards to the malignancy of the breast tumor.

Pre-training:

The ResNet-50 model is pretrained on the ImageNet database, therefore, the feature maps' output proves to be more beneficial for the detection of skin cancer.

4.1.5.2 **Student Model**: Custom CNN

The student model is a fully convolutional network that is less complex than the ResNet-50 and is also smaller in the number of layers it contains in its architecture. The objective of each model is to design a low number of parameters so that the model fits into the memory available on these devices but without assuming a loss of accuracy.

Working of Convolution Neural Networks

The following operations are the various layers/steps of the CNN:

- Convolution
- Pooling
- Flattening
- Full Connection

4.1.5.2.1 Convolution: The first operation or the first step which is convolution operation helps in extracting most of all necessary features from the image. He said that it is a mathematical operation and it is quite evident that it has two inputs an image matrix and a filter or kernel. The filter slides across the image and based on those filter coefficients it multiplies the pixel values and generates feature map.

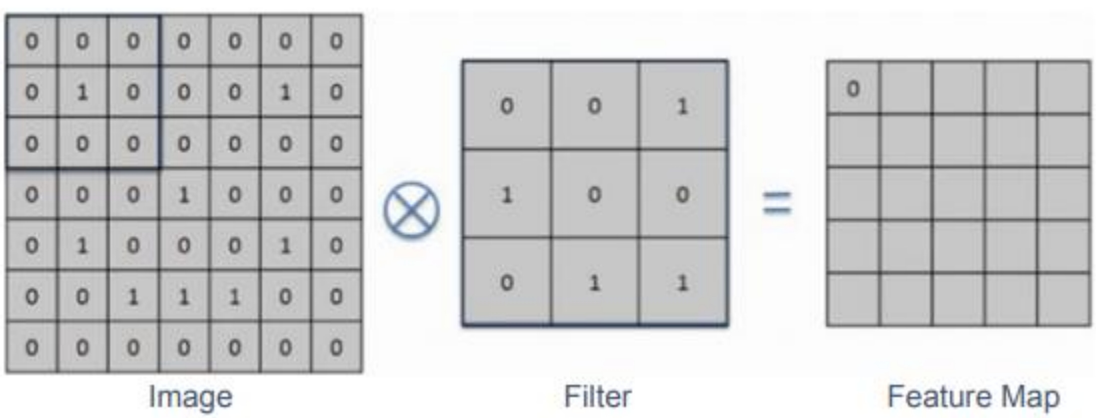


Fig 13. Convolution Operation

It has been explained that convolution operation does lose information but here the idea is to bring down size along with learning integrate. Applying different kind of filters at the time of convolution can help in image enhancement and enhancements such as sharpening an image, detecting edges, blurring images and so on.

4.1.5.2.2 Pooling: Separating dimension operation follows pooling operation because the later helps in minimizing the amount of parameters required in case the size of the image is very large. Subsampling also known as Spatial Down-sampling reduces the size of each feature map though the reduction of dimensions but still preserves important information. Pooling is of basically divided into three types: Pooling is of basically divided into three types:

• Max Pooling (mostly used)

• Sum Pooling

• Average Pooling

Max pooling can be regarded as another form of sample-based discretization method. It is implemented by taking the max filter over the image of size N × N and select the maximum pixel in the particular step and create the feature map. In the same manner, in the average and sum pooling, the average value as well as the sum of the pixel intensities are calculated and taken into the feature map.

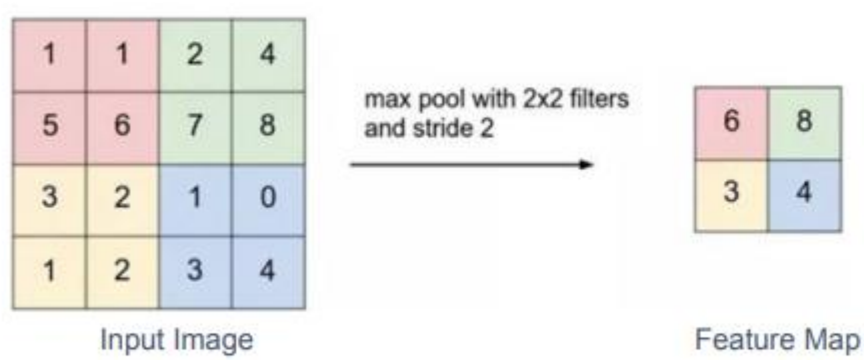


Fig 14. Max polling operation

4.1.5.2.3 Flattening

In order to use our feature maps in to the artificial neural network, we require a simple column vector of the image pixels. In accordance with the name, we can transform our feature maps into a certain kind of column like vector.

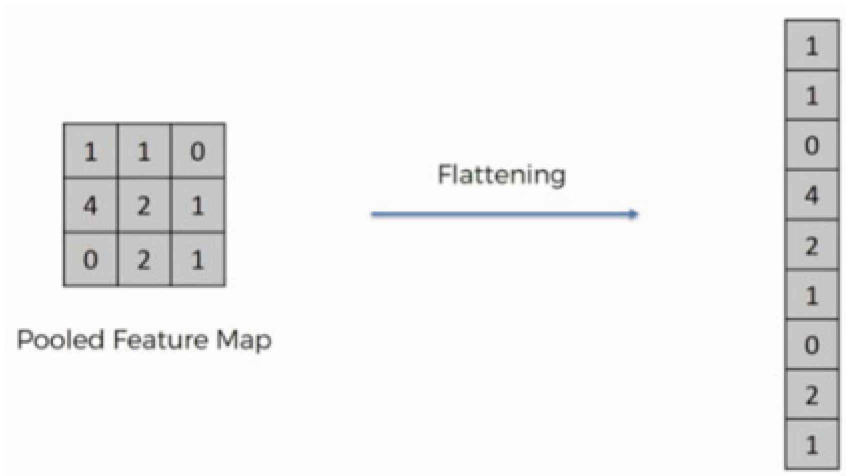


Fig 15. Flattening Process

4.1.5.2.4 Full Connection

The Fully connected layer receives the input from the previous convolution/pooling layer and transforms it into an N vector where N represents the number of classes that the input image must be classified. Therefore, the layer that handles a result decides features most related to a given class based on the neurons' likelihood.

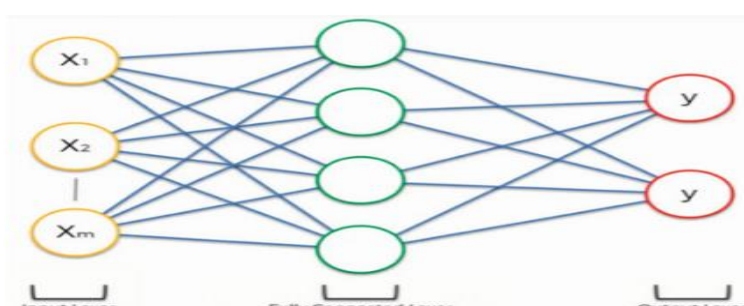


Fig 16. Structure of CNN

Steps followed to build CNN:

- Rescaling Layer - For scaling an input pixel intensity value of a grayscale image from wide dynamic range [0, 255] to a normalized range of [0, 1].
- Convolutional Layer – Convolutional layers continue the input through a convolution filter and seem the result to the next layer. A convolution essentially sums all the pixels in its receptive field into one output, which then produces the feature's value. For instance, when convolving an image, you will be reducing the size of the image, besides, centralizing all the information in the field unto one pixel.
- They are used involving the diminution of the feature maps dimensions without losing the characteristics values. Thus, it minimizes the learning parameters of the region and the overall computation involved in the network. A pooling layer reduces the dimensions of a feature map created by a convolution layer with the aim of exhibiting the features located in a given area.
- Dropout Layer – It is another activation layer type where input units are set to zero with a certain rate at each step during the training phases to minimize overfitting.
- Flatten Layer: For introducing the data to the next layer and in order to make it accepted by the network, the data is flattened into a 1D vector form. It is the exact form interconnection occurs at the designated output layer after all the convolutional layers have been flattened into a single feature vector. And it is linked to the last layer in the system, known as the fully connected layer classification model.
- Dense Layer – The dense layer is the neural network layer that is densely connected, and this implies that every neuron in the major layer is connected to all neurons of the previous layer.
- Activation Function (ReLU) - This is a type of activation function called the rectified linear unit, or ReLU for short, is a linear function with great benefits if the input is positive and if it is negative, the entire formula equates to zero. Re L u is an activation function that has several advantages over the traditional sigmoid and tanh functions: It does not have the vanishing gradient problem, meaning that models can learn and perform much quicker.
- Activation Function (Softmax) - Softmax function is another form of non-linear activation function which is applied at the output layer of the neural network models used to create the of a multinomial probability distribution. The primary benefit associated with the use of Softmax as the activation function of the output layer is to ensure that the output probabilities are reproduced within a range of 0 to 1. Using positive probabilities: The value of positive probability should be

between 0 and 1; the sum of all the positive probabilities be equal to the total probability of one.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling (Rescaling)        (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 178, 178, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 89, 89, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 87, 87, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 43, 43, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 41, 41, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 20, 20, 128)       0
_________________________________________________________________
dropout (Dropout)            (None, 20, 20, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 51200)             0
_________________________________________________________________
dense (Dense)                (None, 128)               6553728
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 9)                 1161
=================================================================
Total params: 6,648,137
Trainable params: 6,648,137
Non-trainable params: 0
```

Fig 17. CNN Model

4.1.5.3 Knowledge Distillation Process

Knowledge distillation entails the forcing of the student model to exhibit the behavior of the teacher model. This is done by minimizing the squared difference of the student's predicted values from the soft targets generated by the teacher model.

Distillation Loss Function:

The loss function used in knowledge distillation is a combination of two components:

- Hard Loss: The accuracy of the model – that is, the extent to which the student's predictions align with the true labels.
- Soft Loss: A metric that evaluates the discrepancy between the numeric values that the student generates and the soft targets developed by the teacher model.

The total loss is given by:

$$\mathcal{L}_{\text{total}} = \alpha \mathcal{L}_{\text{hard}} + (1 - \alpha) \mathcal{L}_{\text{soft}}$$

Where α is a hyperparameter that balances the two loss components.

Soft Targets:

Soft targets are the class probabilities produced by the teacher model, which provide additional information about the relationships between classes. These are obtained by applying a temperature T to the softmax function:

$$q_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

Where zi are the logits from the teacher model, and T is the temperature parameter.

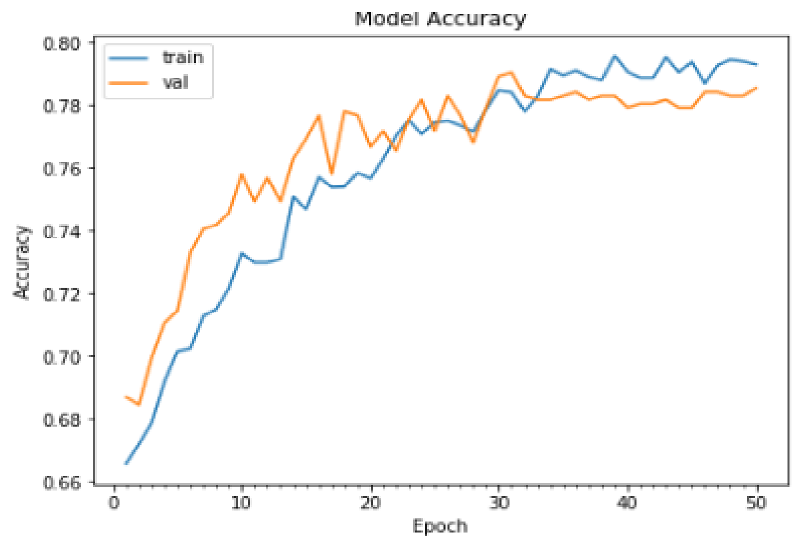
Training Procedure:

1. Train the Teacher Model: Fine-tune the pre-trained ResNet-50 on the skin cancer dataset to obtain high accuracy.
2. Generate Soft Targets: Use the trained teacher model to produce soft targets for the training dataset.
3. Train the Student Model: Train the custom CNN using the distillation loss function, incorporating both hard labels and soft targets.

CHAPTER 5

RESULTS AND ANALYSIS

The dermatologist dataset-based skin cancer detection model further attained an output accuracy of 79. 86%. The results are compared to the teacher model to assess the effectiveness of knowledge distillation. This we have seen also re-emphasize the usefulness of Knowledge Distillation in achieving high results and their applicability in clinical setting.



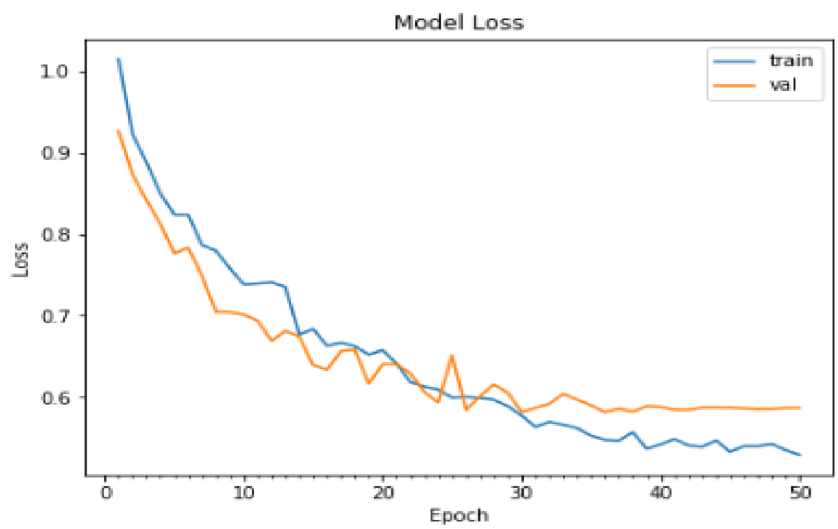


Fig 18. Model accuracy and model Loss

The implementation focuses on the importance of Knowledge Distillation methodologies especially CNNs for the classifications of the various skin cancer lesions type. By employing the Knowledge Distillation-based model for implementing the classification by using a standard and a diverse range of images, the accuracy was 79% that is quite commendable. They are able to attain high accuracy rate in skin cancer identification with an 86% average. These findings highlight the importance of Knowledge Distillation in increasing the level of certainty in diagnostic work, as well as the use of this approach in a therapeutic context. In addition, this study will be added to other ongoing works to develop the effective and accurate skin cancer diagnosis system, which is very important for early diagnosis and, therefore, improvement of patients' prognosis.

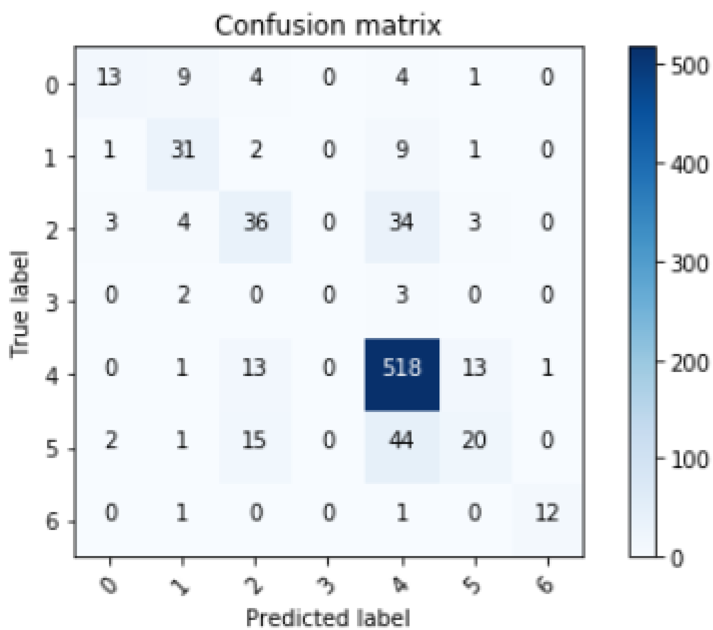


Fig 19. Confusion matrix of the model

CHAPTER 6

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

In applying the Knowledge Distillation approach in the automated skin cancer classification system, the detection accuracies have been boosted. In essence, by deploying knowledge extracted from a big and complicated map to a receptive, though compact map, we are in a position to perform competitively when diagnosing multiple skin diseases, such as skin cancer of various types, melanocytic nevus, and angioma. This method can help doctors optimize their diagnostic efforts by increasing the time taken to correctly diagnose patients, which in turn can improve their survival rates as well as the effectiveness of the treatment processes. In the context of MIA Knowledge Distillation has thus been demonstrated as a rich source of insights that help improve the diagnosis accuracy of the tools developed for the medical field.

Future Scope

Enhanced Model Training: Further work can be done to fine tune the training of the teacher and student models with the goal of increasing the accuracy rate and decreasing the computational time required.

Integration with Clinical Workflows: Assessing and addressing issues on how these automated systems should fit into the clinical processes of delivering care in a way that can easily be embraced by medical practitioners.

Real-Time Diagnostics: Continuous development in the pursuit of the dream of real-time diagnostic tools that can contribute to providing immediate results and responses during a doctor-patient interaction.

Expanded Dataset: Training models with better data sets by including an even bigger and more diverse data set for the training of those who were tested to guarantee that this technique will also work for other races and notably for black and Latin people whose skin is darker.

Multi-modal Data: Applying image data together with other patient attributes including his/her genotype, previous diagnosis and other clinical history to boost a correct diagnosis and unique treatment approach.

Regulatory Approvals: Developing strategies on how to gain approvals to be used in clinical practices and to meet all legal requirements and health care policies present in different jurisdictions.

Social Impact:

Improved Accessibility: The elements touched upon above mean that with the help of automated systems, it will become possible to introduce modern diagnostic equipment in areas where qualified healthcare is limited, and, thus, help eliminate the existing gap in this sphere.

Early Detection and Treatment: These systems thus have an increased potential to detect skin cancer which in turn will contribute to reduced mortality and subsequent improved patient outcomes due to early intervention.

Resource Optimization: The use of automated diagnostics can contribute towards the rational usage of healthcare resources and whilst the aim of diagnostics is to identify potential health concerns, in a way it serves the opposite role of aspiration by minimizing the time and resources needed to diagnose less serious illnesses and leave the more complex cases to be attended to by doctors.

Patient Empowerment: Giving patients better information about their condition and, in a more timely manner, can help them to do more for themselves in terms of treating their illness.

Educational Tools: These systems can also act as an informative teaching aid in the educational institutions for the medical students and doctors, which will give further insight to the physiology of the disease and the diagnosis done.

Cost Reduction: More likely, the use of diagnostic applications can decrease overall medical costs as a result of decreasing the number of unique laboratory tests that are required and misdiagnosis expenses.

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PROOF OF PUBLICATIONS

1. Deeksha Jaiswal "**Advancements in skin cancer detection: A Comprehensive review**" Accepted at the "**International Conference on Artificial Intelligence, Machine Learning and Big Data Engineering (ICAIMLBDE)**" at ISETE, Gurugram.

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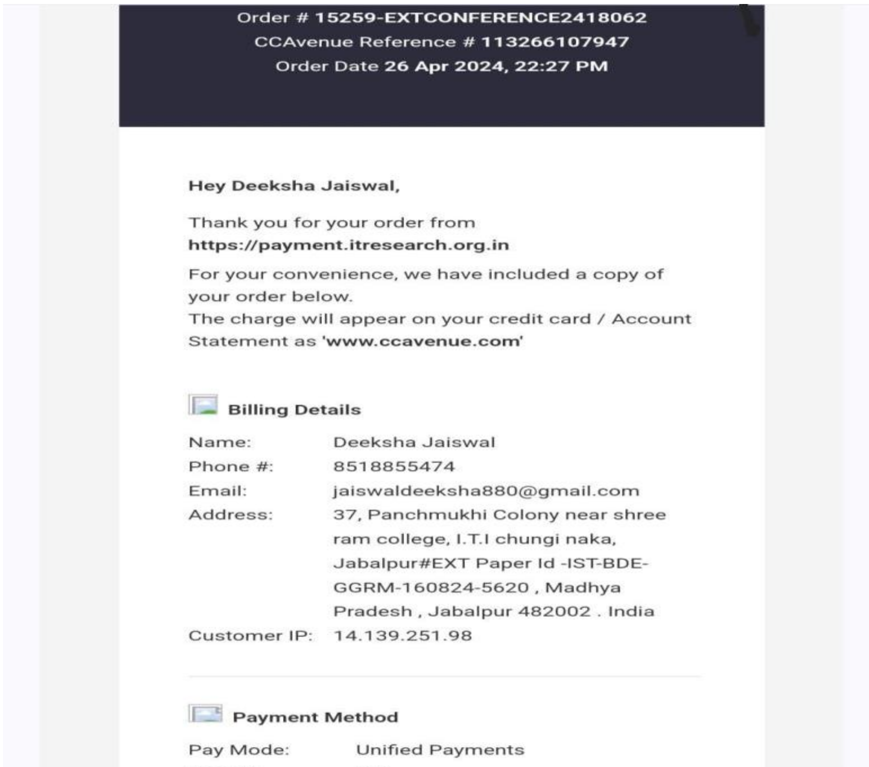
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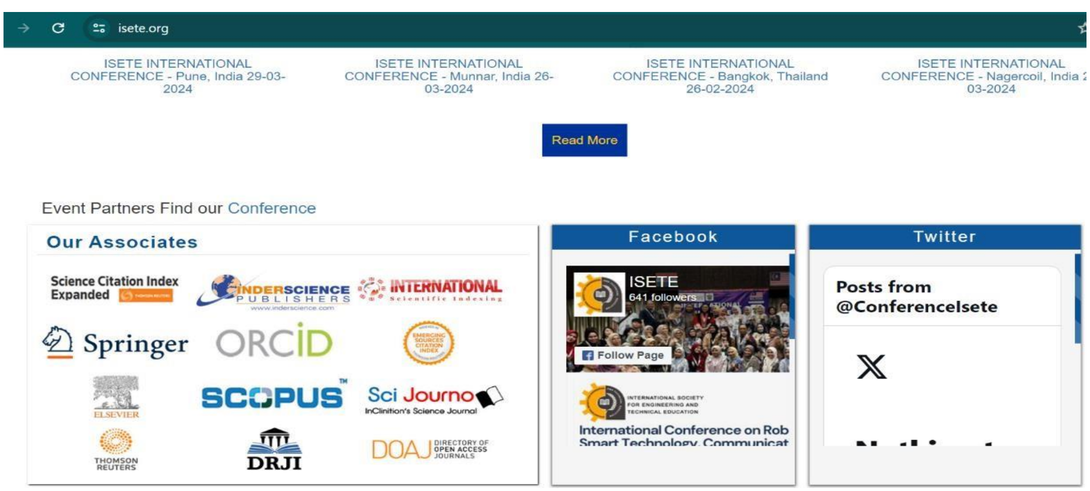

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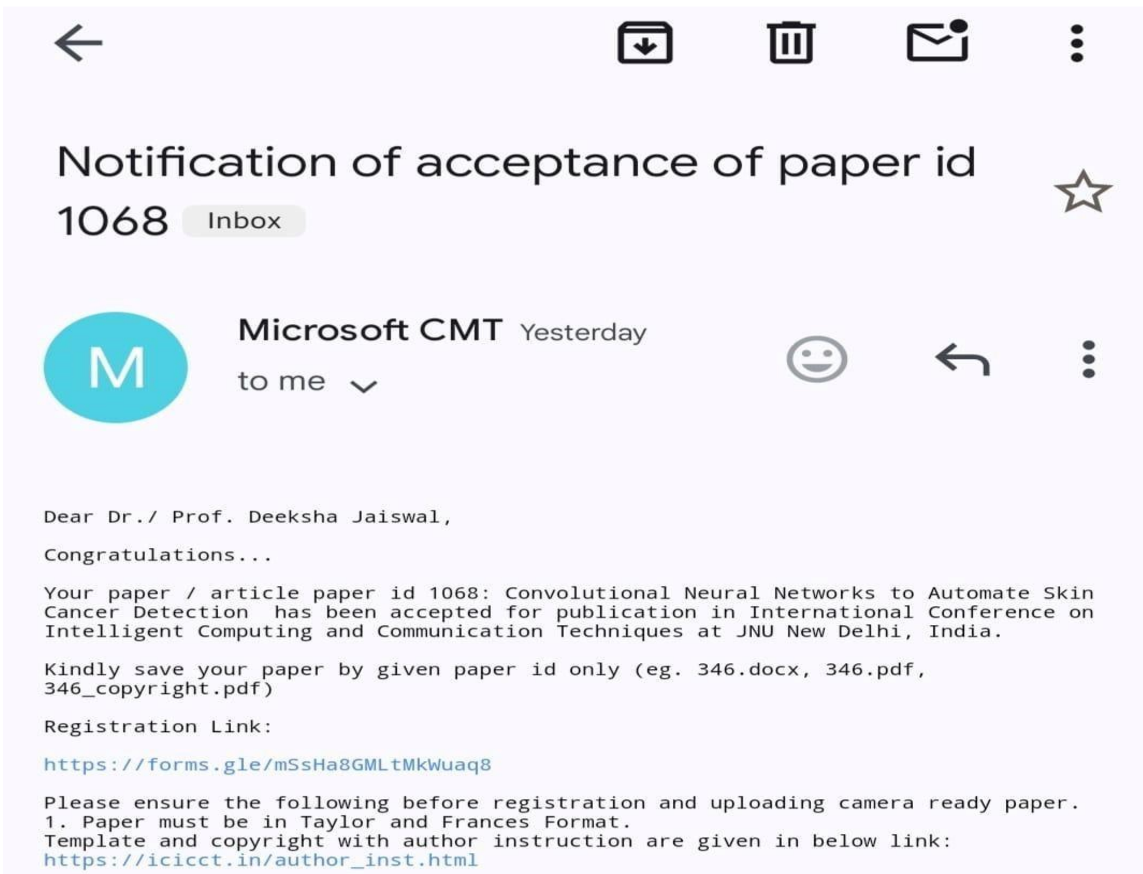

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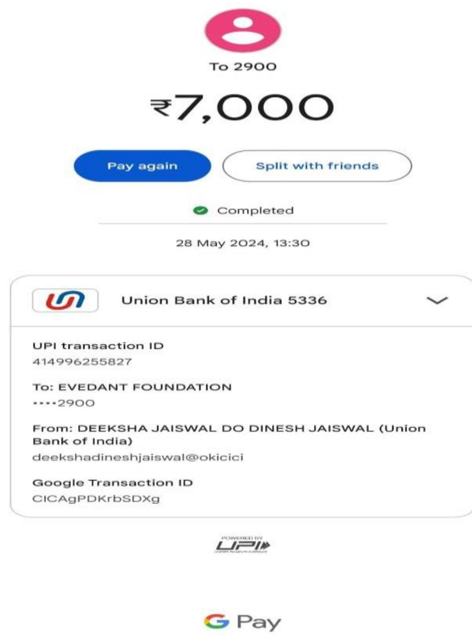

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