A

B. TECH. PROJECT REPORT

On

Skin Cancer Detection System

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology in Information Technology

By

Rahul Patil	**(T2054491246043)**
Prathamesh Shinde	**(T2054491246041)**
Rohan Suryawanshi	**(T2054491246048)**
Ashish Lulla	**(1954491246023)**

Under the

guidanceof

Dr. Bhushan Chaudhari

DEPARTMENT OF INFORMATION TECHNOLOGY

SHRI VILE PARLE KELAVANI MANDAL'S

INSTITUTE OF TECHNOLOGY, DHULE

Survey No. 499, Plot No. 02, Behind Gurudwara, Mumbai-Agra National Highway, Dhule-424001, Maharashtra, India.

Academic Year 2023 – 24

SHRI VILE PARLE KELAVANI MANDAL’S

INSTITUTE OF TECHNOLOGY, DHULE

Survey No. 499, Plot No. 02, Behind Gurudwara, Mumbai-Agra National Highway, Dhule-424001, Maharashtra, India.

Academic Year 2023 – 24

CERTIFICATE

This is to certify that the B.TECH. Project Report Entitled

Skin Cancer Detection System

Submitted by

Rahul Patil	(T2054491246043)
Prathamesh Shinde	(T2054491293041)
Rohan Suryawanshi	(T2054491246048)
Ashish Lulla	(1954491246023)

is a record of bonafide work carried out by him/her, under This guidance, in partial fulfillment of the requirement for the award of Degree of Bachelors of Technology (Information Technology) at Shri Vile Parle Kelavani Mandal's Institute of Technology, Dhule under the Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra. This work is done during semester VIII of Academic year 2023-24.

Date:

Place: SVKM’s IOT, Dhule

Prof. Rubi Mandal	Dr. Bhushan Chaudhari	Dr. Nilesh Salunke
Project Coordinator	**Project Guide & HOD**	**Principal**

Name and Sign with Date	Name and Sign with Date
Examiner -1	Examiner- 2

DECLARATION

We declare that this written submission represents ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Signatures

Rahul Patil	(T2054491246043)	-	____________________
Prathamesh Shinde	(T2054491293041)	-	____________________
Rohan Suryawanshi	(T2054491246048)	-	____________________
Ashish Lulla	(1954491246023)	-	____________________

Acknowledgement

We have immense pleasure in expressing This interest and deepest sense of gratitude towards This project guide and Head of the Department **Dr. Bhushan Chaudhari** for the assistance, valuable guidance and co-operation in carrying out this project successfully and a special thanks to Head of Department. It is a privilege for us to have been associated with This Project Guide, during This B. Tech Project work. We have greatly benefited from his valuable suggestion and ideas. It is with great pleasure that we express This deep sense of gratitude to him for his valuable guidance, constant encouragement and patience throughout this work. We express This gratitude and are thankful to all people who have contributed in their way in making this final year project success. Particularly we want to thank **Prof. Rubi Mandal**, Project Coordinator for This department for making this process seamless for us and arranging everything so perfectly. I take this opportunity to thank all the classmates for their company during the course work and for the useful discussion, I had with them. We take this opportunity to express This heartfelt gratitude towards the Department of Information Technology of Shri Vile Parle Kelvani Mandal's Institute of Technology, Dhule and **Dr. Nilesh Salunke,** Principal of Shri Vile Parle Kelvani Mandal's Institute of Technology, Dhule, that gave us an opportunity for the presentation of this project in the esteemed organization and for providing the required facilities in completing this project. We are greatly thankful to This parents, friends and other faculty members for their motivation, guidance and help whenever needed.

Table of Contents

LIST OF FIGURES

ABSTRACT

Skin cancer is a hazardous type of cancer that can be fatal. To improve the prognosis, skin cancer must be diagnosed early in its early stages. Early skin cancer detection is difficult and costly, though. Cancerous tumors can be difficult to diagnose even when they are apparent since they might resemble benign lesions quite a bit. Examining all pigmented skin lesions surgically can be uncomfortable and cause scars. Thus, the requirement for an automatic and painless skin cancer detection system with high accuracy. Machine Learning (ML) and Deep Learning (DL) have shown promise in skin cancer detection. This paper compares the effectiveness of several DL models, including ResNetv2, VGG16, EfficientNet-B5, and EfficientNet-B7, using pre-trained Convolutional Neural Networks (CNNs), with a ML model, Support Vector Machine (SVM), to determine if a skin sample is cancerous. The results demonstrate that the CNN models outperform the SVM in accuracy, precision, recall, and F1-score, with EfficientNet-B7 achieving the highest F1-score of 84.22%...

Keywords: Skin Cancer, SVM, CNN, Deep Learning, Machine learning.

1. INTRODUCTION

It has been acknowledged that skin cancer is one of the most common illnesses in the globe since the 1970s. It is defined by an extremely great multiplication of skin cells that are biologically abnormal. Melanoma is the most common kind of skin cancer that can be triggered by malignant tumors, which have a tendency to spread rapidly. Over the past few decades, there was an obvious increase in the number of persons diagnosed with both melanoma and non-melanoma skin cancer. A significant portion of skin cancer situations are triggered by melanoma, in particular, which is a serious condition. The World Health Organization (WHO) predicts that one in three Americans will be affected by skin cancer in the next years. A separate research carried out by the Skin Cancer Foundation (SCF) indicates that this percentage might rise to one in five persons. Skin cancer incidence has also increased in western nations as well, such as Australia and Canada. Skin cancer, especially melanoma and non-melanoma variations, is a severe health concern that may severely hamper normal physical processes. In 2018, there were one million incidences of non-melanoma skin cancer and over 300,000 cases of melanoma globally. It is expected that these figures will rise to 2,450,000 in the next 20 years. Mortality from skin cancer is closely linked to the disease's stage. For instance, the overall survival rate for people with melanoma is around 98.4%; however, it drops to 22.5% in cases of metastatic melanoma. Early identification and treatment is critical because as the condition worsens, the death rate tends to rise. Dermatologists usually make the diagnosis of skin cancer by examining the patient's skin for benign or malignant lesions. But it can be difficult to differentiate between the two kinds of lesions; therefore, a radiologist's skill is required for a precise diagnosis. Numerous reasons, such as viruses, inflammation, environmental factors, allergies, and infections, can result in skin cancer. Although there are therapies for skin cancer, those who receive a diagnosis early on tend to have the highest survival rates. The skin acts as a barrier to protect the body's internal organs, and any abnormalities in skin function can point to underlying problems, including skin cancer. Early discovery of cancer of the skin stages can enhance the outcome of patients, hence it is so important to precisely diagnose the stage of cancer. A delayed diagnosis can drastically diminish the likelihood of survival. Numerous techniques, including support vector machines (SVM), Neural Networks (NN), K-Nearest Neighbors (KNN), and Naive Bayes (NB), have been employed by scientists to forecast the disease's early stages. Low error rates, high efficiency, and accurate prediction outcomes have been achieved with these methods. Machine learning (ML) and deep learning (DL) models are used in many different areas, such as robotics, healthcare, hospitality, and agriculture, due to their better prediction of outcomes skills. For the purpose of to predict skin cancer, this study used a variety of pre-trained algorithms, especially those that classified pictures either as harmless or cancerous. Four different classifiers were applied in order to accomplish the classification: SVM, KNN, NB, and NN.

1.1. Motivation

The detection of cancer, located in different part of human body, is not a new problem. From the previous decades, doctors use innovate machines to capture the potentially part of body in which can exist abnormality. Doctor examine the abnormality and determine if it is cancer using their knowledge and experience. To detect skin cancer, which is one of the most common type of cancer, doctors examine the lesion and decide the type (malignant or benign). If the lesion evaluated as malignant, the patient follows the biopsy process, which is a painful process. Its trigger our mind to think how the current technology and especially machine learning can provide humans an easily access application which classify the lesion given an affordable second option before follow the infallible biopsy process.

Skin cancer is a very difficult problem with a lot of challenges since it is associated with visual media and medical science. The possible solutions are limited by the current technology and the deficit of dermoscopic images. In the future, the new knowledge in the field of image processing and machine learning algorithms, and also the expansion of the skin cancer dermoscopic image dataset can help us tackle the problem more efficiently and accurately, making right and proper decisions. But the enrich of image dataset is the most challenging task since these record are privacy so our model need to fulfill this need and does not reveal any information which can be used to identify the person. we deal with the problem of the Skin Cancer detection by examining different approaches related with image pre-processing, feature extractions, and classification models. features for our predicted model, Support-Vector-Machine and decision trees to classify the input images.

1.2. Aims and Objectives:

Aim:

The skin cancer detection technology is broadly divided into four basic components, viz., image pre-processing which includes hair removal, de-noise, sharpening, resize of the given skin image, segmentation which is used for segmenting out the region of interest from the given image. Feature extraction features are extracted using two dimensional wavelet, Image enhancement techniques change the pixels' intensity of the image so as the output images to looks better.

Objectives:

The central goal of this project is to create a precise and dependable system for skin cancer detection model. By harnessing advanced computational techniques and meteorological data, the objective is to improve our comprehension of skin lesions and, in turn, enhance the accuracy of predictions regarding their attack. The project's core objectives revolve around developing a robust skin cancer detection model. Beginning with thorough data collection and pre-processing, the project aims to identify key features influencing skin lesions, incorporating advanced machine learning algorithms for accurate predictions. Integration of remote sensing technologies, user-friendly visualization tools, and real-time monitoring for early warnings are key components. The skin cancer detection technology is broadly divided into four basic components, viz., image pre-processing which includes hair removal, de-noise, sharpening, resize of the given skin image, segmentation which is used for segmenting out the region of interest from the given image. Feature extraction features are extracted using two dimensional wavelet, Image enhancement techniques change the pixels' intensity of the image so as the output images to looks better.

1.3 Scope:

The scope of project on skin cancer detection model involves the comprehensive development of a system that leverages advanced computational techniques and meteorological data. Key components include data collection, pre-processing, and the identification of critical features influencing cyclone intensity [8]. The project extends to the creation and optimization of machine skin cancer detection Using Deep Learning Technique learning algorithms tailored for skin cancer detection model, The potential for leveraging deep learning in the detection of skin cancer is immense, promising significant advancements in early diagnosis and treatment. By training convolutional neural networks (CNNs) on extensive datasets of dermoscopic images, these models can accurately differentiate between benign and malignant lesions, often exceeding the diagnostic capabilities of dermatologists. Such models are capable of analyzing visual attributes like texture, color, and shape, identifying intricate patterns associated with various skin cancers, including melanoma, basal cell carcinoma, and squamous cell carcinoma. Implementing these models can greatly enhance teledermatology services by providing swift, remote, and reliable assessments, especially in regions with limited access to specialist care. Additionally, deep learning-based diagnostic tools can support continuous monitoring and patient follow-ups, facilitating personalized treatment plans and potentially easing the burden on healthcare systems. Integrating these models into smartphone apps and wearable devices could broaden access to skin cancer screening, encouraging early detection and saving lives. Furthermore, advances in explainable AI within deep learning can improve the transparency and reliability of these models, aiding their adoption in clinical environments.

2. LITERATURE SURVEY

The skin lesion is detected and classified into Melanoma skin cancer type or normal skin type. To detect cancer part the region of interest is extracted from the images. The various images of skin as well as images of cancer are used to detect and classify Melanoma skin cancer. Initially pre-processing is done on image using median filtering. With the help of median filtering the unwanted part of skin image is removed. After applying median filtering smooth image is obtained. Segmentation is applied on smoothed image[3]. Median filtering is necessary because unwanted portion of an image can reduce the accuracy of classification. For pre-processing histogram equalization technique can be used. In histogram equalization there are two methods one is global histogram equalization and another is local histogram equalization. Global histogram equalization considers overall image while in Local Histogram technique small portion of an image is considered. In Histogram Equalization technique intensity values are mapped into definite intensity levels. To have contrast enhancement of an image histogram equalization technique is used. But here rather than histogram equalized image on original histogram of an image Thresholding method is used because for original histogram the higher accuracy results are obtained than the histogram equalized image[7]. After segmentation features are extracted using wavelet transform and then skin cancer portion is detected and classified accordingly. One of the most deadly and fatal types of cancer is malignant melanoma. Despite the fact that only 4% of the population is diagnosed with cancer, this is a problem which accounts for 75% of all deaths caused by it. Cancer of the skin if melanoma is detected early enough, it can be treated. Treatment can be administered if the disease is detected early. Melanoma is treatable if caught early, but it is fatal if caught late. Melanoma has the potential to spread deeper into the skin and cause serious complications. It can also affect other regions of the body, making it an extremely dangerous situation. treatment is challenging the presence of melanin causes melanoma.

Melanocytes are pigment-producing cells found throughout the human body[9]. Melanoma is caused by skin exposure to UV radiation, which is one of the main causes. Dermo copy is a technique for examining the structure of the skin. An approach based on observation can be used to detect dermo copy images of melanoma the precision of the dermo copy is dependent on the dermatologist's training[10]. The Melanoma detection accuracy can range between 75% and 85%. Despite the fact that dermo copy is used by skin professionals as a procedure for diagnosis. The system's diagnosis is going to be accurate[11]. Assist in improving the diagnostic' speed and accuracy. The computer will be able to retrieve some data, such as asymmetry, color variation, and texture characteristics are all examples of minute details. Human eyes may not be able to recognize certain parameters. An automated dermo copy image analysis has three stages.

(a) Image Pre-Processing (b) Segmentation (c) Extraction

The most important aspect is segmentation significant and also plays an important part because it influences the process of future phases. It appears that supervised segmentation is simple, to put into practice by taking into account criteria such as shapes, sizes, and colors and hues, as well as skin types and textures[12]. This system-based analysis will shorten diagnosis time and improve accuracy. The precision Dermatological diseases have a significant mortality rate. One of the most challenging aspects is the complexity, variety, and scarcity of knowledge. tough terrains in order to make a rapid, simple, and accurate diagnostic Particularly in developing and developing countries with a limited healthcare budget Furthermore, it is widely knowledge that the. In many diseases, early detection minimizes the odds of death of grave consequences recent environmental issues have influenced worked as a stimulant for the development of various skin disorders[13]. The following are the stages of these diseases in general: STAGE 1- in situ diseases have a survival rate of 99.9%, STAGE 2- diseases with a high-risk level have a survival rate of 45- 79 percent, STAGE 3-regional metastasis has a survival rate of 24-30 percent, and STAGE 4- distant metastasis has a survival rate of 7-19 percent. Skin is the largest organ of the integumentary system and consisted of seven layers of tissues. The skin is the outer part of the human body forming a shield which helps to cover the different system of human structure such as the muscular, skeletal (bones and ligaments) and internal organ system. Skin cancer is one of the most common cancer in the world, and the medical record deduce that skin cancer is the most common type of cancer in many countries. Sun can easily harm our skin and as a result skin cancer is primarily detected on areas of skin which highly exposed to

The sun, but it is also formed on areas that seldom see the light of day. The functions of skin are very important for the survival of human, so the development of abnormal cells on any skin layer can be harmful for the organism and might affect other parts of the body since it is detached to other organs and tissues and cancer can be spread more easily. Compared to the other two types of skin cancer, melanoma is the deadliest cancer although it is the least common type. Melanoma reported as the deadliest form of skin cancer since it is responsible 75% of all skin cancer deaths. The early detection of the melanoma is essential, since it enn be treated and finally cured in its early stages[15] However, if the diagnosis becomes late, it is difficult to cured and can be hazardous to the health, since it grows deeper into the skin and spread to other tissues and organs. So, it is important to examine our existing moles, freckles, bumps, and birthmarks to detect possible abnormality in early stage. This lead us to invest more time to improve skin cancer detection algorithms, which is more advantageous to patients compared to the traditional biopsy method[18]. The cases of this disease show that skin cancer can affect people of all races, including those with darker complexions. Current research in the discipline of skin cancer detection using artificial intelligence has a limitation affiliated with the non white population. This restriction leads us to expand the current skin cancer classification models using dermoscopic images from people with different skin tones to train the models. This improvement generates an application which appeal to the whole population.

Over the years, a continuous evolution related to cancer research has been performed. Scientists used various methods, like early stage screening, so that they could find different types of cancer before it could do any damage[20]. With this research, they were able to develop new strategies to help predict early cancer treatment outcome. With the arrival of new technology in the medical field, huge amount of data related to cancer has been collected and is available for medical research. But, physicians find the accurate prediction of the cancer outcome as the most interesting yet challenging part. For this reason, machine learning techniques have become popular among researchers. These tools can help discover and identify patterns and relationships between the cancer data, from huge datasets, while they are able to effectively predict future outcomes of a cancer type.

2.1 Key Limitations of machine learning algorithms

ML has profoundly impacted the world. We are slowly evolving towards a philosophy Varval Noah Harari calls "dataism", which means that people trust data and algorithms more than their personal beliefs.

think this definitely couldn't happen to you, consider taking a vacation in an unfamiliar . Let's say you are in Zanzibar for the first time. To reach your destination, you Blow the GPS instructions rather than reading a map yourself. In some instances, people e plunged full speed into swamps or lakes because they followed a navigation device's instructions and never once looked at a map.

ML offers an innovative approach to project development that requires processing a large amount of data. But what key issues should you consider before you choose ML as a tool to develop for your startup or business? Before implementing this powerful technology, you mas be aware of its potential limitations and pitfalls. ML issues that may arise can be classified in five main categories, which we highlight below.

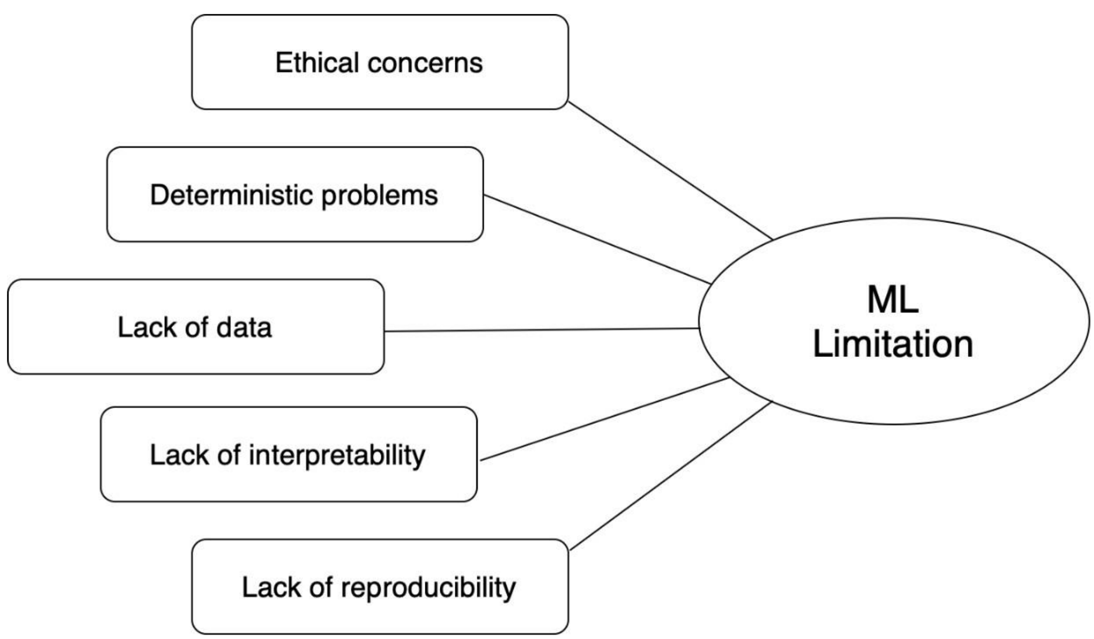

Fig. 2.1 Limitations of existing system

Ethical Concerns

There are, of course, many advantages to trusting algorithms. Humanity has benefited from computer algorithms to automate processes, analyze large amounts of data, and make couples chevisions. However, trusting algorithms has its drawbacks. Algorithms can be subject to baas at any level of development. And since algorithms are developed and trained by humans, it's nearly impossible to eliminate bias.

Many ethical questions still remain unanswered. For example, who is to blame if something goes wrong? Let's take the most obvious example self-driving cars. Who should be held accountable in the event of a traffic accident? The driver, the car manufacturer, or the developer of the software?

One thing is clear- AML cannot make difficult ethical or moral decisions on its own. In the the distant future, we will have to create a framework to solve ethical concerns about ML technology.

Deterministic Problems

ML is a powerful technology well suited for many domains, including weather forecasting and climate and atmospheric research. ML models can be used to help calibrate and correct sensors that allow you to adjust the operation of sensors that measure environmental indicators like temperature, pressure, and humidity.

Models can be programmed, for example, to simulate weather and emissions into the atmosphere to forecast pollution. Depending on the amount of data and the complexity of the model, this can be computationally intensive and take up to a month.

Can humans use ML for weather forecasting? Maybe. Experts can use data from satellites and weather stations along with a rudimentary forecasting algorithm. They can provide the necessary data like air pressure in a specific area, the humidity level in the air, wind speed, etcetera, to train a neural network to predict tomorrow's weather.

However, neural networks do not understand the physics of a weather system, nor do not understand its laws. For example, ML can make predictions, but the calculations of such intermediate fields as density can have negative values that are impossible under the laws of
physics. Al does not recognize cause-and-effect relationships. The neural network finds a mention between input and output data but cannot explain the reason they are connected.

Lack of Data

Neural networks are complex architectures and require enormous amounts of training data to produce viable results. As the size of a neural network's architecture grows, so does its data requirement. In such cases, some may decide to reuse the data, but this will never bring good necks.

Another problem is related to the lack of quality data. This is not the same as simply not having data. Let's say your neural network requires more data, and you give it a sufficient quantity, but you give it poor quality data. This can significantly reduce the model's accuracy.

For example, suppose the data used to train an algorithm to detect breast cancer uses mammograms primarily from white women. In that case, the model trained on this dataset might be biased in a way that produces inaccurate predictions when it reads mammograms of Black women. Black women are already 42% more likely to die from breast cancer due to many factors, and poorly trained cancer-detection algorithms will only widen that gap.

Lack of Interpretability

One significant problem with deep learning algorithms is interpretability. Let's say you work for a financial firm, and you need to build a model to detect fraudulent transactions. In this case, your model should be able to justify how it classifies transactions. A deep learning algorithm may have good accuracy and responsiveness for this task but may not validate its solutions.

Or maybe you work for an Al consulting firm. You want to offer your services to a client that uses only traditional statistical methods. Al models can be powerless if they cannot be interpreted, and the process of human interpretation involves nuances that go far beyond technical skill. If you can't convince your client that you understand how an algorithm comes to a decision, how likely is it that they will trust you and your experience?

It is paramount that ML methods achieve interpretability if they are to be applied in practice.

Lack of Reproducibility

Lack of reproducibility in ML. is a complex and growing issue exacerbated by a lack of code transparency and model testing methodologies. Research labs develop new models that can be quickly deployed in real-world applications. However, even if the models are developed to take into account the latest research advances, they may not work in real cases.

Reproducibility can help different industries and professionals implement the same model and discover solutions to problems faster. Lack of reproducibility can affect safety, reliability, and the detection of bias.

3. PROPOSED SYSTEM

This section explains proposed system of this project. Before starting the analysis of our project, a diagram of the process which is followed in order to complete our design, is represented. The following diagram can help us to describe more clearly the functions that were implemented at each stage to reach our goal.

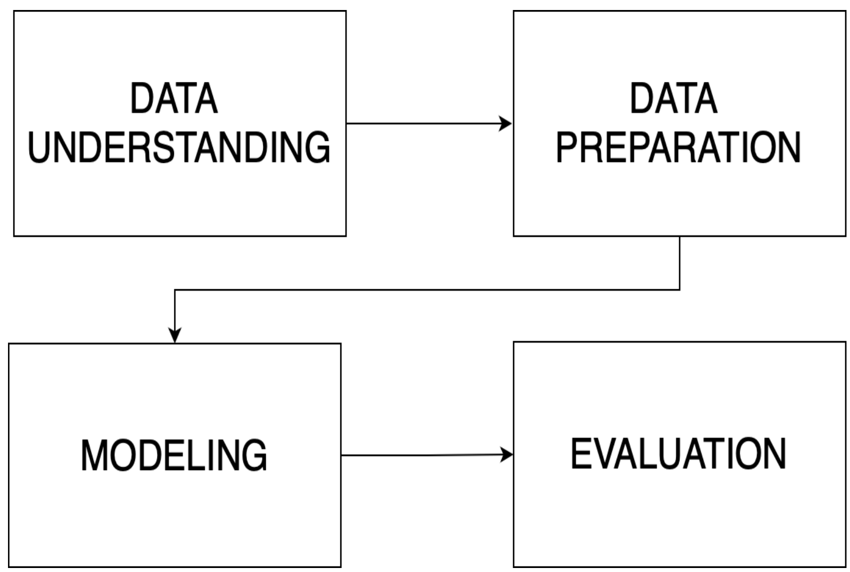

Fig. 2 Proposed System

It is obvious, that the stage of Data Understanding is the most vital. Data Understanding combines the subdivided stages of Data Requirements, Data Collection and Dain Understanding. Before starting the collection of data, we need to clearly understand the problem that is needed to tackle, and specify all the requirements for our project. These requirements help us to determine the sources and the methods that we have to use in order to collect the appropriate data. At this fust stage of the process, the creation of the database is stand, by collecting all data needed, which consist of the initial data. Following this, we have to clearly understand the content of the input data and identify noise that may be included. For our implementation, it is obvious that dermoscopic images are the necessary input that must be obtained in order to move to the next stage. It is important that, these images should be labeled and confirmed from expert as benign and malignant to ensure the amices of the project. Furthermore, these images needed to be captured with a scope or a high resolution camera in order to depict the lesion in detail. It is an evidence that these images can contain noise. The most common type of noise, is hairs, which exist in many part of human skin. Data Preparation is the most necessary stage of the process, since the input image is transformed to useable data. Once the data has been collected, we need to process the data, to reduce the existing noise and extract information, to create the final database for modeling stage. The data preparation is a very time-consuming procedure since the implementation of different algorithms needed to improve and transform the initial database. In this stage some features are extracted, in order to classify the lesion and as a consequence, existing noise can corrupt the final decision. It is prerequisite to build an efficient image processing stage, stacking many image filters to reduce the noise. Modeling refers to the purpose of data mining. After the stage of data collection and preparation, the data must be handled by an appropriate model. Depending on the data mining problem a afferent appropriate model exists. The selection of the appropriate model is a demanding sk, while the usage of the final result depends on it. The correct models reveal patterns and cures that provide meaningful insights and new knowledge. For our project, these patterns and structures can lead to a classification of the lesion into two categories: benign and malignant.

Evaluation is the last and most important stage. During this stage, the selected model is tested by a preselected part of the database. This, allow one to see the effectiveness and the accuracy of the model. Results from this stage, are used to determine if it is mandatory to return in one of the previous stages in order to follow a different approach and alter the requirements of our project. This feedback can lead to more appropriate results. The results of this stage lead us to spend more time in data pre-processing stage applying additional filter to reduce noise and to improve the accuracy of the models.

Image Acquisition

The process of collecting or obtaining an image from a camera so that it may be transmitted through other processes that must occur later is known as image acquisition. In image processing, picture acquisition is the initial stage in the workflow sequence because no further processing is feasible without an image.

Image Pre processing

1) The first step in pre-processing is the enhancement of the image by modification of both Contrast and

Brightness (reduce light illumination). Contrast is described as the modification in color or luminance that marks an object making it distinct and unique in the image. The higher the difference between a pixel and its neighbors the higher the contrast is in that area. Brightness can be described as the sensitivity produced as a result of the luminance of a visual mark. In image processing of pixels, a bright pixel is characterized by a higher value. We therefore modified our images by applying a scale factor and delta to the scaled values to perform enhancements.

2) Color Space: The HSV (Hue, Saturation, and Value) color space, unlike the RGB (Red, Green and Blue) color space which is the format of the acquired image from a standard camera, is a cylindrical color space. The Hue values are across a circle. So, after completing one rotation across the circle, we get the same color i.e. the Hue values at 0 and 360 represent the same color as illustrated in Fig. below.
HSV color space usually gets better information for image processing. This is because it splits color data (Chroma) from intensity or lighting (Luma). Therefore, generating a histogram or thresholding procedures is likely using only saturation and hue as a result of the value being divided through color data splitting. We used the first channel which represents luminance is the HSV format converted images. This format of the image is also a type of grayscale that makes it possible to extract contours by double thresholding.

Image Enhancement

The purpose of this stage is to increase visibility of the feature of interest, based on our project, the adjustment and enhancement of the contrast is needed. Image enhancement techniques change the pixels' intensity of the image so as the output images to looks better. It an important step to prepare the image for threshold stage and the GLCM method. The result of this stage is to make more sharpen the image border and improve the brightness. After applying this filter, it is easier to separate the background and the object of interest which is depicted. Nowadays, there are many image enhancement techniques suitable for different tasks with specific requirements. The most used methods are classified into Linear and Non-Linear contrast enhancement techniques. In our implementation, the histogram equalization method to improve the image enhancement is selected. The above images are an example where the result of this filter to the histogram of the image can be observed.
The histogram equalization is the most common method for image enhancement, since its simplicity and better performance with all types of images, compared to other existing methods. Histogram equalization replaces the output image with uniform distribution of pixel and it flattens and stretches the

image. The operations of the Histogram Equalization are performed by remapping the gray levels using the cumulative distribution of the input gray levels. The step of the implementation of this algorithm is simple. The first step is to calculate the histogram of the image. After that we use the cumulative distribution function and the normalization of this function gives the output image. The general histogram equalization formula is the following:

$$h(v) = round\ (cdf(v) - cdf(min)\ M * N - cdf(min)) * (L-1)$$

Equation 1

where cdf(min) is the minimum value which occur from the cumulative distribution function, MN is equal to the pixel of image and the L is equal to the number of gray levels. In our case the L take the value of the 256 since the initial image converted to grayscale and the pixels' value range is from 0 to 256. The equalization formula scales the values of the grayscale pixels from 0 to 255.

Image Segmentation

The purpose of image segmentation stage is to separate the background and the lesion by wing the image to binary and depict the area of interest. This stage is dominant for our mentation, since the binary Image is used for extracting the most features from the AD role. There are many approaches to implement this filter. Some of them combine bine learning algorithms in order to locate the region of interest, separating from the Aground and other more simply methods, called thresholding algorithms, segment the image There are many thresholding algorithms. Among them, the Otsu's and global thresholding method have been distinguished. The main difference between these two apposes, is that the Otsu's algorithm performs automatic image thresholding. It searches for the most efficient thresholding value that minimizes the intra-class variance instead of the global algorithm which requires a predefined value of the threshold. Finding the global thresholding value could be an easy task, if the background and the area of interest have distinguished values of brightness in the grayscale image. The global thresholding method is quite easy for implementation. In this method the value of each pixel is checked and replaced with a white pixel if the intensity is greater than the global thresholding value or with a black pixel if the pixel's value is less. From the thresholding process the output is a white background and a black area for the lesion. Another essential step in the stage of segmentation, is the inversion of the pixel's values of the image. The inverted image is necessary for the implementation of the morphological filter. In order to extract some of the features of the ABCD rule, some functions of the OpenCV library are used. Black background to locate the region of interest with white color is required by these functions.

Noise Removal

This stage focuses on the removal of noises which arisen in the process of capture and the hairs that exist on human body. The detection and removing of unwanted noise is a highly demanding process since an algorithm is needed for separating the real features of an image and the features which are create the noise. The noise can corrupt true information of the image, having serious affect to final result. In bibliography, different filters to reduce noises from dermoscopic images are used. The first filter called Gaussian blur and smooths an image using a Gaussian function. It is a low-pass filter which removes the noise level and insignificant details by blurring the image. This is achieved be applying a Gaussian kernel. The second filter is called Median filter which is widely used in projects related with skin cancer since it can prevent edges. In these projects, the Median Filter is selected, since edges invariant is a key factor to extract correct features from ABCD rule. The median filter is a non-linear filter and it is commonly used in image processing. The appealing characteristic of this filter is the conservation of the edges and the ability of reducing impulse noise. The median filter sorts the pixel's values and take the median value under the kernel area and replace the central pixel with this median value. Different approaches use kernel with different size and shape since the reduction of noise depends on these. This is an important disadvantage. If the number of pixels which is characterize as a noise is greater than N(N+N)/2 and the kernel size is NxN, then the noise cannot be deleted, as a result we need to increase the size of the kernel. On contrast, if the number of noise pixels is smaller than N(N+N)/2 and the kernel size is NxN, then the pixel's values can corrupt since the algorithm assign irrelevant values, as a result we need to decrease the size of the kernel. To clearly understand the algorithm, we illustrate below an analytic example of a median filter using a 3x3 kernel.

Feature Extraction

For Melanoma cancer features resides within the border of lesion. These features are ed on classification algorithm to classify cancer images and skin images. It is essential to act important features so that the classification results will be improved. The features are tected using two dimensional wavelet. An original image is divided into four parts at first el of devompesition [8]. Each part represents feature and two level of decomposition is e to obtain the features, In second level of decomposition out of four parts again each part divided into four parts so total 16 parts are generated. Six parameter are used for features peration so total 96 features are generated. From Figure it has been observed that high pass and low pass filters are applied on image. Output of low pass filter gives approximation of an original image. At second level of decomposition an output of low pass filter contains finer details than first level of decomposition. The different types of wavelets are used and results re obtained. The features are obtained using parameters like mean, median, standard deviation, minimum, variance and maximum. The accuracy depends on type of wavelet The features in one dimension cannot be detected while in second dimensions important data can be revealed. Fourier transform gives only frequency information of an image while wavelet is used to get information about frequencies as well as temporal information of it. Using two dimensional wavelet information about how the frequencies are used as well as when exactly they have to use is obtained.

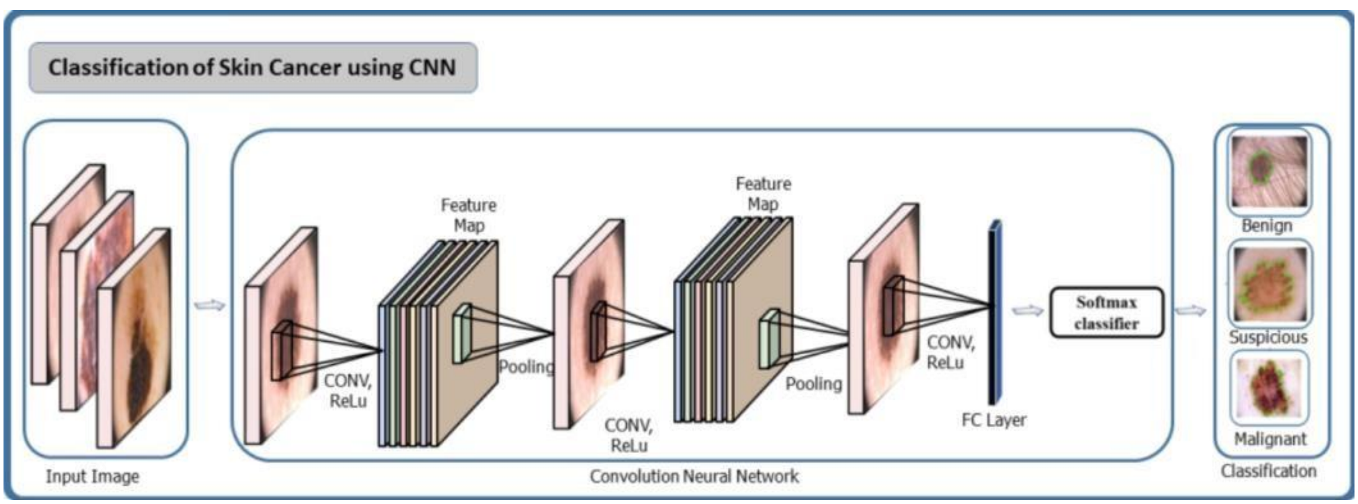

Fig. 3 Feature Extraction

Architecture

To discover the most efficient detection and classification of melanoma skin cancer into malignant and benign skin cancers, we used three distinct methods in our model: Neural Networks, Support Vector Machines, and Convolutional Neural Networks. The pre-processed data is then segmented, and feature extracted, with the retrieved feature images being fed into Neural Networks and Support Vector Machines to categorize the images as cancerous or benign and predict the exact accuracy.

Neural Networks

In the neural Networks we have used the Back Propagation Algorithm. The Back Propagation is a supervised learning algorithm, for training the multi-layer perceptron's. while designing the neural networks we initialize the weights with some random values as we do not know what exactly the weight can be, so we first give some random weight if the model provides an error with large values. so, we need to need to change the values to somehow minimize the error value. To generalize this, we can just say,

- Calculate the error How far is your model output from the actual output.
- Minimum Error Check whether the error is minimized or not.
- Update the parameters If the error is huge then, update the parameters (weights and bases). After that again check the error. Repeat the process until the error becomes minimum.
- Model is ready to make a prediction Once the error becomes minimum, you can feed some inputs to your model and it will produce the output. The Backpropagation algorithm looks for the minimum value of the error function in weight space using a technique called the delta rule or gradient descent. We are trying to get the value of weight such that the error becomes minimum. Basically, we need to figure out whether we need to increase or decrease the weight value. Once we know that, we keep on updating the weight value in that direction until error becomes minimum. You might reach a point, where if you further update the weight, the error will increase. At that time, you need to stop, and that is your final weight value.

Convolution Neural Networks

CNNs are neural networks with a specific architecture that have been shown to be very powerful in areas such as image recognition and classification. CNNs have been demonstrated to identify faces, objects, and traffic signs better than humans and therefore can be found in robots and self-driving cars CNNs are neural networks with a specific architecture that have been shown to be very powerful in areas such as image recognition and classification. CNNs have been demonstrated to identify faces, objects, and traffic signs better than humans and therefore can be found in robots and self-driving cars CNNs are neural networks with a specific architecture that have been shown to be very powerful in areas such as image recognition and classification. CNNs have been demonstrated to identify faces, objects, and traffic signs better than humans and therefore can be found in robots and self-driving cars. CNNs are neural networks with a specific architecture that have been shown to be very powerful in areas such as image recognition and classification. CNNs have been demonstrated to identify faces, objects, and traffic signs better than humans and therefore can be found in robots and self-driving cars. CNNs are a supervised learning method and are therefore trained using data labeled with the respective classes. Essentially, CNNs learn the relationship between the input objects and the class labels and comprise two components: the hidden layers in which the features are extracted and, at the end of the processing, the fully connected layers that are used for the actual classification task. Unlike regular neural networks, the hidden layers of a CNN have a specific architecture. In regular neural networks, each layer is formed by a set of neurons and one neuron of a layer is connected to each neuron of the preceding layer. The architecture of hidden layers in a CNN is slightly different. The neurons in a layer are not connected to all neurons of the preceding layer, rather, they are connected to only a small number of neurons. This restriction to local connections and additional pooling layers summarizing local neuron outputs into one value results in translation-invariant features. This results in a simpler training procedure and a lower model complexity.

Data preparation

The first step is cropping the input images so as to reduce the noise that is displayed at the corners. After some experiments, it is concluded that the correct percentage of cropping $% for each dimension. To be more precise, 4% of the initial pixels are cropped of each Inde. After cropping the image, it is necessary to convert the RGB image to Grayscale image, Figure B. For this conversion the equation (6.1), which is described in data preparation chapter, is used. To reduce the noise, the Median Filter with a 3x3 kernel size is selected. This selection is based on the ability of Median filter to prevent the edges. Observing the Figure C, it is noticed that the hairs are reduced.

The input image for the GLCM method is the results of the histogram equalization filter. The histogram equalization filter increases the adjustment of the image. The goal of this filter is to scale the pixels' values in the range [0,255]. After this step the area of lesion is emphasized. The results image is the D image that is displayed in Figure. The next step is to segment the image, using thresholding techniques. The Otsu's method is firstly selected, but after some experiments is concluded that, the global thresholding method achieves the same results, since the selection of thresholding value is an easy process, due to the fact that, the pixel values of the lesion are distinct from the background. To be more specific, the thresholding value is 100. As a result, the ability of the Otsu's method to find the propel thresholding value is unnecessary. The binary image is shown on the Figure 8.1-E. It can be seen that, the background is white and the lesion area is black. Some functions of the OpenCV, which are used to extract some features values, in order to work properly, require a black background and a white lesion area. One of the most important function is the cv2.findContours which is used to locate the lesion area. So, the inverted image is necessary for our implementation. The result image after this stage is represent at Figure F.

From the inverted image, it is noticed that some noise is still existing, so a further Image process is required. To improve the thresholding stage and reduce the existed noise, the open morphological filter is added to the process. The selected kernel size for open filter is 5x5. As already described in Chapter 6, the open filter uses an erode filter to reduce the size of the white objects included the lesion. To reconstruct the lesion to the initial size, the dilation filter is applied. Figure G depicts that the noise of the previous picture is almost removed. The input image for the image preparation process. This image is the initial RGB image which is displayed in the Fig. This image is classified as malignant.

One of the most important steps in our project is the values of the extracted features. With this features the initial database of images is converted to the final tabular database, which is red to train the classifications models. The values of the extracted features of the two different images are represented below. One of these images is classified as a malignant, while the other image classified as benign. By using the ABCD rule and the GLCM method, x and four features are extracted correspondingly. To extract the ABCD rule, the OpenCV library is mainly used. The cv2.findcontours function returns the boundary of the lesion. Using this contour, we can calculate the centroids and the perimeter of the lesion. Also, with contours we can calculate the area of the lesion and the diameter. The border irregularity is calculated by using the perimeter and the area. To calculate the asymmetric, functions from the numpy library are used. Color variegation values are calculated by using the initial RGB image, instead of other extracted features that use either grayscale enhancement image or binary image. To extract the GLCM features we use the greycomatrix function which is provided by the skimage library. Furthermore, to extract each features from the result of the previous function we use the greycoprops which is also provided by the skimage library.

UML diagram

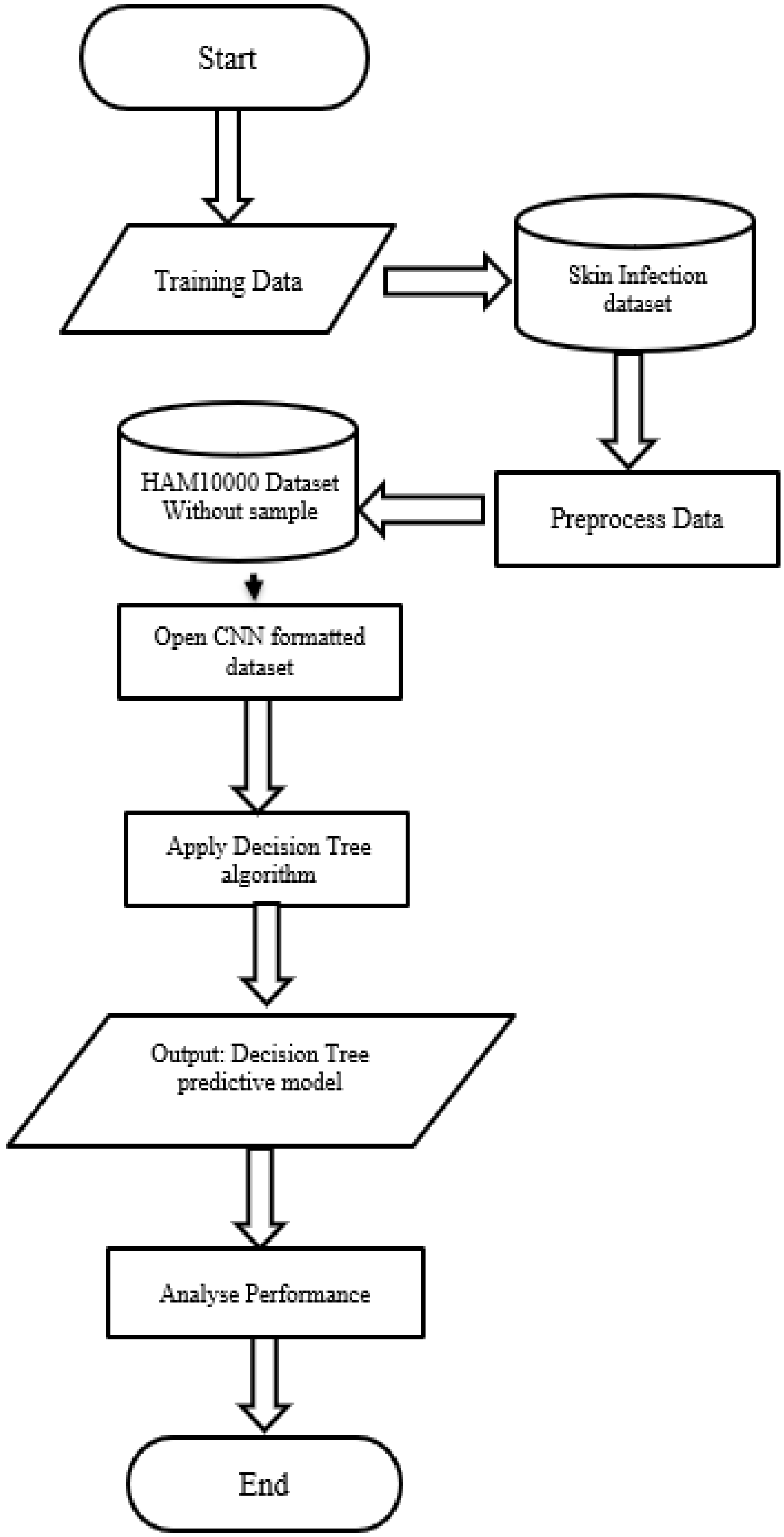

Fig. 4 UML Diagram

Details of Existing System

Programming Language

Our project is developed using python programming language. Python is a clear and powered object-oriented programming language. By using Python, many common programming tasks can easily be developed, since a large standard library is supported. These standard libraries facilitate the creation of different programs related with image processing apolations like cropping, image segmentation, classification and features extractions, which are predominant tasks for our implementation. An additional appealing feature is that, many new and advanced tools, related to image processing, are available for free. All these masons make the python programming language an appropriate choice for developing image processing and machine learning task, Image pre-processing Libraries. In order to implement this project, the first goal is the reduction of noise and the adjustment of contrast. Many python image pre-processing libraries, like Scikit image, NumPy, PIL/Pillow and OpenCV we used. Especially, OpenCV library is used for both image processing and feature extraction stage. A briefly overview of the usage and functionality of these libraries is made below:

Scikit Image

Scikit-image consist of many algorithms for image processing. It is an open source Python package that primarily works with NumPy arrays. By using the available algorithms of this library, applications used in different fields such as research, education and industry can be developed. Scikit-image focuses on being the reference library for scientific analysis related with image processing. It is a fairly simple and straightforward library. Every function comes with detailed documentation and examples that describe how each function is used in an application. This code is of high-quality and peer-reviewed. Algorithm's codes are written by volunteer developers, who are members of the active community. This library is of high- quality and peer reviewed since all the included algorithms are tested by core developers to ensure correctness. A primary mission is to care for users' data, meaning that the code doesn't modify input arrays unless explicitly directed to do by the user. The package is imported as skimage and most functions are found within the submodules.

NumPy

NumPy is one of the fundamental libraries in Python programming and provides support for arrays. It is independent on any other Python packages and it only depends on an accelerated linear algebra library.

This library uses MATLAB-style syntax to perform numerical operations. It is widely used for image processing applications, since an image is essentially an array structure, consisting of data points that represent pixels. Therefore, by using basic NumPy operations, such as slicing, masking and fancy indexing, the pixel values of an image can be easily modified and the desire output image can be achieved. Numpy is commonly used to mask an image. In order to use this image library, it is mandatory to load the initial image by using skimage library and display the preprocessing image with matplotlib library.

PIL/Pillow

PIL (Python Imaging Library) is a free library included in python programming language which supports opening, manipulating, and saving many different image file formats, with the ability to create new file decoders to expand the library. However, its development has stagnated, with its last release in September 2009 which supports Python 1.5.2-2.7. The following years, the Pillow project has forked the PIL repository and added Python 3 support. As a consequence, the original PIL has been replaced and is available for all major operating systems (Windows, Mac OS X, and Linux). This library contains basic image processing functionalities, including per pixel operations, masking and transparency handling, filtering with a set of built-in convolution kernels, and color space conversions.

Technologies used

HTML: HTML is the standard markup language for creating Web pages. HTML stands for HyperText Markup Language. HTML describes the structure of Web pages using markup. HTML elements are the building blocks of HTML pages. HTML elements are represented by tags.

CSS: Cascading Style Sheets (CSS) is a style sheet language used for describing the presentation of a document written in a markup language such as HTML, CSS is a cornerstone technology of the World Wide Web, alongside HTML and JavaScript, CSS is designed to enable the separation of presentation and content, including layout, colors, and fonts. This separation can improve content accessibility; provide more flexibility and control in the specification of presentation characteristics; enable multiple web pages to share formatting by specifying the relevant CSS in a separate css file, which reduces complexity and repetition in the structural content, and enable the ess file to be cached to improve the page load speed between the pages that share the file and its formatting.

JavaScript: JavaScript is a lightweight, interpreted programming language. It is designed for creating network-centric applications. It is complementary to and integrated with Java. JavaScript is very easy to implement because it is integrated with HTML. It is open and cross-platform.

Django: Django is a high-level Python web framework that encourages rapid development and clean, pragmatic design. Built by experienced developers, it takes care of much of the hassle of web development, so you can focus on writing your app without needing to reinvent the wheel. It's free and open source.

TensorFlow: TensorFlow is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks. TensorFlow was developed by the Google Brain team for internal Google use in research and production. The initial version was released under the Apache License 2.0 in 2015. Google released the updated version of TensorFlow, named TensorFlow 2.0, in September 2019.

Design Details

1. Categorization of needs in 3 components.
   a. The Frontend.
   b. The Logic
   c. And the Backend.
2. The Logic is component which works as connection between the Frontend and the Backend and perform operations on it.
3. It is a Machine Learning based web app so it will also have the ML models and Algorithms in it to perform operations on the data.
4. Here, the frontend is handled by the popular JS framework and for Tailwind CSS will be used for custom styles due to its modularity.
5. The backend will be mostly handled by Flask, a very popular python web framework library.
6. The logic operations primarily the ML operations will be performed by using TensorFlow python library and MobileNet.

   The MobileNet model is ideal for mobile and embedded vision applications as they have lightweight DNN architecture. We used MobileNet convolutional neural network it pretrained on 12,80,000 images containing 1,000 object classes from the 2014 ImageNet Challenge. The 25 layered MobileNet architecture was constructed for the current study, which employs four Conv2D layers, seven Batch Normalization layers, seven ReLU layers, three ZeroPadding2D layers, and single DepthwiseConv2D, Global Average Pooling, Dropout, and Dense layers.

```
import cv2
import numpy as np
from matplotlib.pyplot import imread
from matplotlib.pyplot import imshow
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.imagenet_utils import decode_predictions
from tensorflow.keras.applications.imagenet_utils import preprocess_input

img_path = '16.jpg'
```

Sequential is the easiest way to build a model in Keras. It allows you to build a model layer by layer. We use the 'add()' function to add layers to our model. Our first 2 layers are Conv2D layers. These are convolution layers that will deal with our input images, which are seen as 2-dimensional matrices.

The ReLU function is another non-linear activation function that has gained popularity in the deep learning domain. ReLU stands for Rectified Linear Unit. The main advantage of using the ReLU function over other activation functions is that it does not activate all the neurons at the same time.

With the help of Sigmoid activation function, we are able to reduce the loss during the time of training because it eliminates the gradient problem in machine learning model while training.

We use train_test_split() to get training and test sets. Control the size of the subsets with the parameters train_size and test_size. Determine the randomness of your splits with the random_state parameter. Obtain stratified splits with the stratify parameter. With this function, we don't need to divide the dataset manually. By default, Sklearn train_test_split will make random partitions for the two subsets.

Sklearn provides a very efficient tool for encoding the levels of categorical features into numeric values. LabelEncoder encode labels with a value between 0 and n_classes-1 where n is the number of distinct labels. If a label repeats it assigns the same value to as assigned earlier.

Keras Image Data-Generator class provides a quick and easy way to augment your images. It provides a host of different augmentation techniques like standardization, rotation, shifts, flips, brightness change, and many more.

However, the main benefit of using the Keras Image Data-Generator class is that it is designed to provide real-time data augmentation. Meaning it is generating augmented images on the fly while your model is still in the training stage.

Image Data Generator class ensures that the model receives new variations of the images at each epoch. But it only returns the transformed images and does not add it to the original corpus of images. If it was, in fact, the case, then the model would be seeing the original images multiple times which would definitely overfit our model.

We perform train data function and found 6898 validated image filename belonging to the 7 classes. and test data function found 1703 validated image filenames.

Methodology

Machine Learning

In machine learning there are 2 different modes namely training mode and testing mode.

Histogram

A histogram is an exhibit of genuine information that uses lines to show the repeat of data things in dynamic numerical between times of identical size. A Histogram is a graphical introduction of data using bars of different statures. It is used to shorten discrete or reliable data that are assessed on a break scale. Right when the components are unending, there are no openings between the bars in any case, in discrete case gaps should be left between the bars. From the histogram we calculate the mean value (M). Now using mean value, we need to calculate the suitable equation for displaying the output. On trying different equation, we can conclude that cubic regression holds good for displaying the result.

Mobilenet

MobileNet is a CNN architecture that was developed by researchers at Google in 17 that is used to incorporate Computer Vision efficiently into small, portable devices like mobile phones and robots without significantly reducing accuracy. The total number of ammeters in a standard MobileNet is 4.2 million, which is significantly lesser than some of the other CNN architectures. MobileNets also give model developers the flexibility to control the size of their model(at the cost of accuracy) depending on their requirements by introducing two new global hyperparameters that can be tuned according to the requirements of the model developer.

Depthwise Separable Convolutions

In mobilenets, depth wise separable convolutions are used in place of standard convolutions to reduce the size and complexity of the model.

A depthwise separable convolution is performed on a given input image in two steps:

1. Depthwise Convolution
2. Pointwise Convolution

Depthwise Convolution

In Depthwise Convolution, a seperate filter is applied to every channel of the input image individually. Assuming that the input image is of dimension D F^ * D F^ * M(where M is the number of channels), we would require M filters of dimension D_{K}*D_{K} * 1 (It should be noted that each filter will be applied to only one channel of the input image). After applying a depthwise convolution on the input image, we will get M matrices of dimension (D_{F} - D_{K} + 1) * (D_{F} - D_{K} + 1) * 1 When these matrices are stacked together, we get a single resulting output matrix of dimension (D_{F} - D_{K} + 1)(D_{F} - D_{K} + 1) * M

Pointwise Convolution

The pointwise convolution layer applies 'N' filters of dimension 1 * 1M on the output of the Depthwise Convolution layer. This results in an output image of dimension (D_{F} - D_{K} + 1) × (D_{F} - D_{K} + 1) * N (The purpose of using |* 1 filters is to increase the number of channels of the output image).

Hence the total cost of computation would be D_{K}D_{K}*M(D_{F} - D_{K} + 1)(D_{F} - D_{K} + 1) + M x N(D F^ - D_{K} + 1)*(D F^ - D K +1).

Network Structure

A single Mobilenet layer looks like

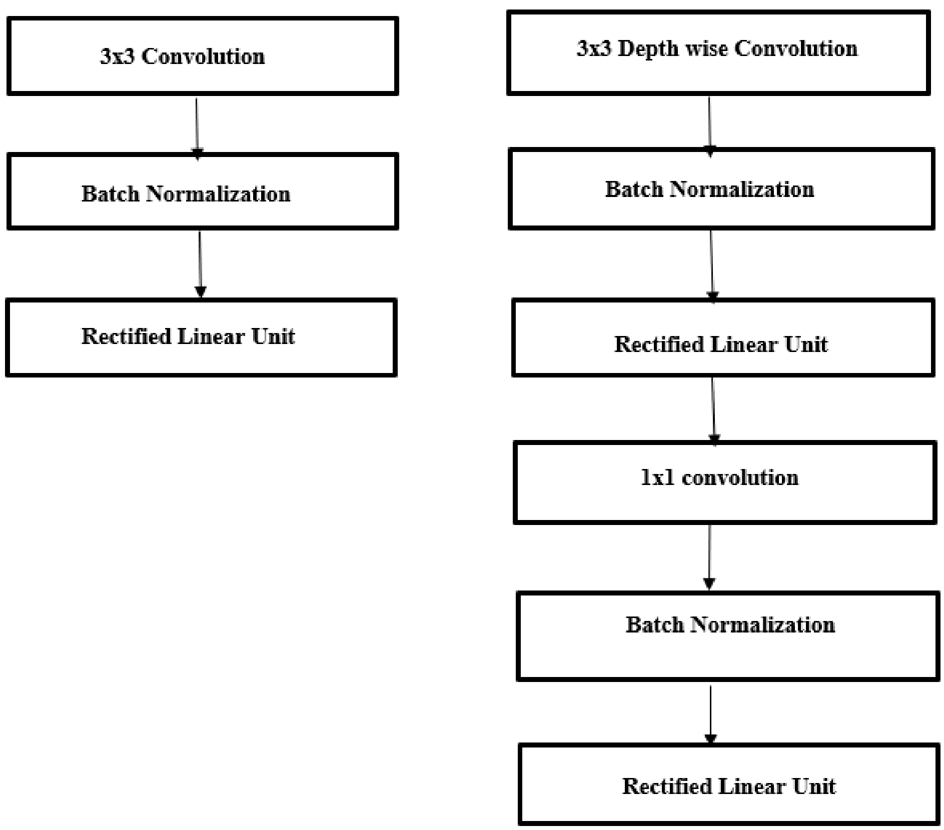

Fig 5 Network Structure

4. Experimentation and Results

Details of dataset

In order to solve the issue of training neural networks for automated diagnosis of pigmented skin lesions owing to the small size and lack of diversity in current data sets, the HAM10000 ("Human Against Machine with 10000 training images") dataset was made accessible. Dermatoscopic pictures across a range of demographics were collected and obtained through multiple techniques to create this set of images.

Diverse methods were used for gathering data and cleaning, and for ensuring diversity, semi-automatic processes using specifically trained neural networks were created. The final dataset, 10015 dermatoscopic images, is meant to be used in academic machine learning and is freely available through the ISIC the archive. You may use this comparison dataset to contrast stuff with people. This benchmark dataset can be used for comparisons with human experts as well as machine learning activities.

The dataset includes a wide range of significant criteria for diagnosis for pigmented lesions. Over fifty percent of the lesions have been verified by pathology, and the basis of truth for the other instances has been determined by follow-up, expert agreement, or live confocal imaging.

```
history = model.fit(
    train_gen,
    validation_data=valid_gen,
    epochs=100
)
```

```
pd.DataFrame(history.history)[['accuracy','val_accuracy']].plot()
plt.title("Accuracy")
plt.show()

pd.DataFrame(history.history)[['loss','val_loss']].plot()
plt.title("Loss")
plt.show()
```

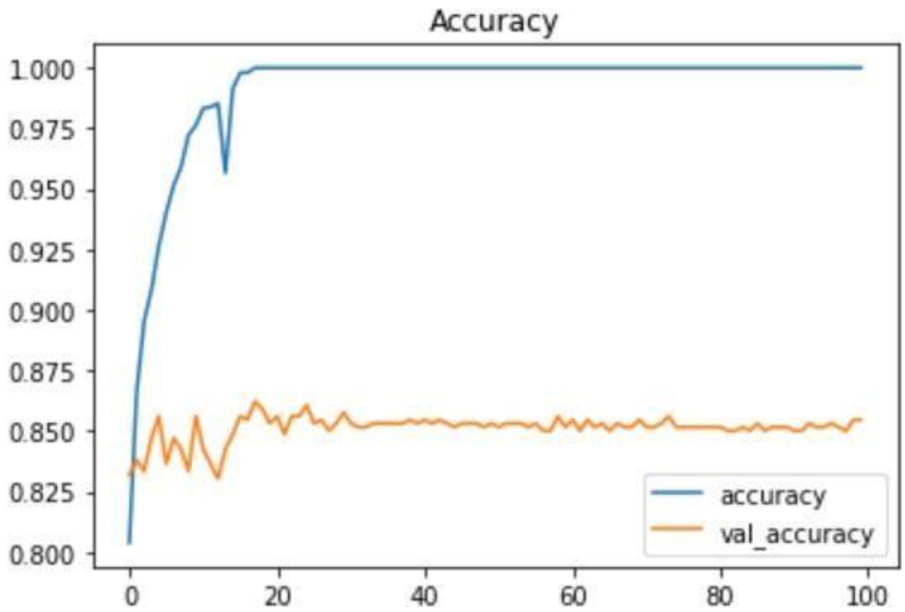

Fig. 6 Model Accuracy

The pyplot API in matplotlib, which was first developed as a free successor to MATLAB, provides an easy stateful interface akin to MATLAB. Sometimes individuals consider the Object-Oriented (OO) API to be more complicated to use, even if it is more powerful and adaptable. The pyplot interface thus becomes frequently utilized and used as the default.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Equation 2

In terms of both positive and negative outcomes, accuracy for binary categorization can also be calculated using the following method:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

Equation 3

Where, TP = TRUE POSITIVES, TN = TRUE NEGATIVES , FP = FALSE POSITIVES ANDFN = FALSE NEGATIVES

```
pd.DataFrame(history.history)[['accuracy','val_accuracy']].plot()
plt.title("Accuracy")
plt.show()

pd.DataFrame(history.history)[['loss','val_loss']].plot()
plt.title("Loss")
plt.show()
```

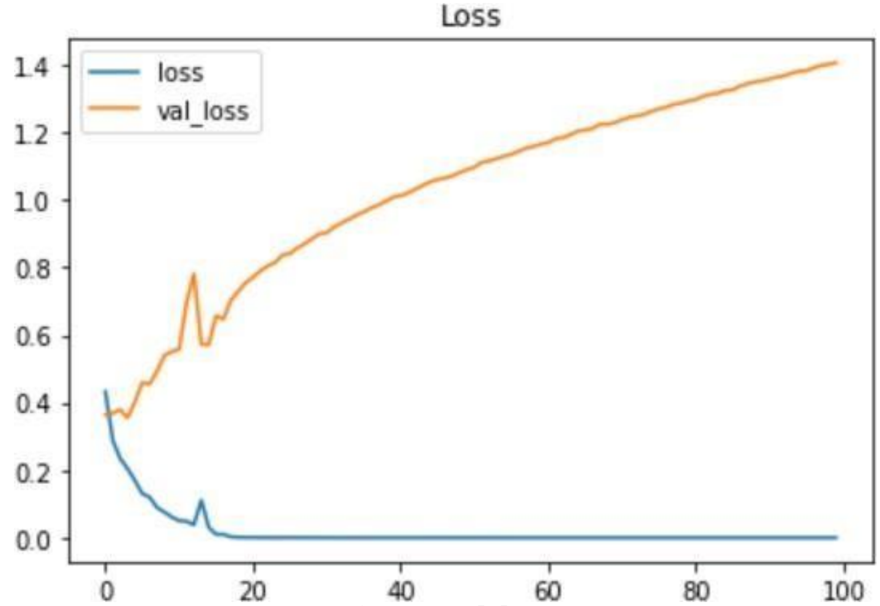

Fig. 7 Model Loss

Machines can acquire novel skills through lowering a loss function that assesses how well an algorithm illustrates the given data. When predictions and actual results diverge considerably, a high number is generated by the loss function. In time, optimization processes enable the loss function to reduce errors in prediction. This article covers the various loss coefficients and their uses in machine/deep learning.

Almost each algorithm in machine learning utilizes the exact same function of loss. The choice of loss function is affected by the kind of machine learning method, how simple it is to calculate derivatives, and, to a certain extent, whether or not there are any outliers in the dataset.

```python
import cv2
import numpy as np
from matplotlib.pyplot import imread
from matplotlib.pyplot import imshow
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.imagenet_utils import decode_predictions
from tensorflow.keras.applications.imagenet_utils import preprocess_input

img_path = '16.jpg'
```

Fig. 8 Loading an Image

```python
img = cv2.imread(img_path)
img = cv2.resize(img, (100, 100))

x = np.expand_dims(img, axis=0)
x = preprocess_input(x)
result = loaded_model_imageNet.predict(x)
print((result*100).astype('int'))
```

Fig. 9 Prediction

```python
p=list((result*100).astype('int'))
pp=list(p[0])
print(pp)
```

[31]

```
... [0, 100]
```

Fig. 10 Calculation

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread(img_path)
imgplot = plt.imshow(img)
plt.title(name_class[index])
plt.show()
```

Fig. 11 Plotting

5. FEASIBILITY STUDY

The feasibility study serves as the cornerstone of any project, providing a comprehensive assessment of its viability and potential success. In this study, we delve into various aspects including technical, economic, operational, and scheduling feasibility to ascertain the practicality of our proposed project. Through meticulous analysis and evaluation, we aim to determine whether the project aligns with organizational goals, budgetary constraints, and resource availability. By identifying potential challenges and risks upfront, we can strategize mitigation measures and ensure a smooth execution, ultimately enhancing the project's chances of achieving its objectives.

1. Introduction

Skin cancer is one of the most common cancers globally, with millions of new cases diagnosed each year. Early detection significantly improves treatment outcomes and survival rates. This study explores the feasibility of developing a skin cancer detection system using advanced technologies such as artificial intelligence (AI) and imaging techniques.

2. Market Analysis

2.1 Market Need:

Increasing incidence of skin cancer worldwide.

Rising awareness of the importance of early detection.

Demand for non-invasive, quick, and accurate diagnostic tools.

2.2 Target Audience:

Dermatologists and healthcare providers.

Patients at risk of skin cancer.

Research institutions and universities.

2.3 Competitive Landscape:

Existing diagnostic tools: Dermatoscopes, biopsy methods.

Emerging technologies: AI-powered diagnostic tools, mobile apps for self-assessment.

3. Technical Feasibility

3.1 Technology Overview:

Imaging Devices: High-resolution cameras, dermatoscopes.

AI Algorithms: Machine learning models trained on large datasets of skin images to identify cancerous lesions.

Software: Development of a user-friendly interface for healthcare providers and patients.

3.2 Development Process:

Data Collection: Curating a large dataset of labeled skin images.

Model Training: Training AI models to distinguish between benign and malignant lesions.

Validation: Rigorous testing and validation to ensure accuracy and reliability.

Deployment: Integration with existing healthcare systems and mobile platforms.

3.3 Challenges:

Ensuring high accuracy and minimizing false positives/negatives.

Obtaining a diverse and comprehensive dataset.

Regulatory approvals and compliance with healthcare standards.

4. Operational Feasibility

4.1 Infrastructure Requirements:

High-performance computing resources for AI model training.

Secure cloud storage for data.

Reliable and scalable software infrastructure.

4.2 Personnel:

Dermatologists for data annotation and model validation.

AI and software engineers for development and maintenance.

Regulatory experts for navigating approvals.

4.3 Implementation Timeline:

Phase 1: Research and data collection (6 months).

Phase 2: AI model development and testing (12 months).

Phase 3: Software development and integration (6 months).

Phase 4: Pilot testing and regulatory approval (12 months).

Phase 5: Full-scale deployment (6 months).

5. Financial Feasibility

5.1 Initial Investment:

Hardware and software development costs.

Personnel salaries and consulting fees.

Data acquisition and storage expenses.

5.2 Operational Costs:

Maintenance of the system.

Continuous data updates and model retraining.

Marketing and user support services.

5.3 Revenue Model:

Subscription-based model for healthcare providers.

One-time purchase or freemium model for mobile app users.

Licensing agreements with research institutions.

5.4 Cost-Benefit Analysis:

Reduced healthcare costs due to early detection and treatment.

Improved patient outcomes and survival rates.

Potential market size and revenue projections.

6. Risk Analysis

6.1 Technical Risks:

Model accuracy and generalization to diverse populations.

Data privacy and security concerns.

6.2 Operational Risks:

Integration with existing healthcare systems.

User adoption and acceptance.

6.3 Financial Risks:

High initial investment with uncertain return on investment.

Competition from established diagnostic tools and methods.

7. Conclusion and Recommendations

The study indicates a promising potential for developing a skin cancer detection system leveraging

AI and imaging technologies. The benefits of early detection and improved patient outcomes outweigh the risks and challenges identified. Further steps should include detailed project planning, securing funding, and initiating pilot testing.

6. CONCLUSION

The skin cancer incidences are intensifying over the past decades, the need of an hour is to move towards an efficient and robust automated skin cancer classification system, which can provide highly accurate and speedy predictions. In this study, we demonstrated the effectiveness of deep learning in automated dermoscopic multi-class skin cancer classification with the MobileNet model trained on a total of 38,569 dermoscopic images from HAM10000 dataset. We matched the performance of expert dermatologists across seven diagnostic tasks with an overall accuracy of 83.1% for seven classes in the dataset, whereas top2 and top3 accuracy of 91.36% and 95.34%, respectively. Also, the weighted average of precision, the weighted average of recall, and the weighted average of fl-score were found to be 89%, 83%, and 83%, respectively. We conclude that MobileNet model can be used to develop an efficient real-time computer-aided system for automated medical diagnosis systems. As compared to previously proposed models the MobileNet model has shown accurate and robust performance in addition to its faster and lightweight architecture. The future work may deal with the utilization of patient's personalized data such as genes, age, color in addition to the current study for skin cancer diagnosis. This additional feature can be advantageous to develop personalized computer-aided systems for the diagnosis of skin.

REFERENCES

1. V. R. Allugunti, A machine learning model for skin disease classification using convolution neural network."The International Journal of Computing, Programming and Database Management, vol. 3, no. 1, pp. 141–147, 2022; "
2. M. S. Junayed, N. Anjum, A. Sakib, and M. B. Islam presented "A deep CNN model for skin cancer detection and classification." doi: 10.24132/ csrn.2021.3101 At the WSCG'2021 - 29. International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision'2021, 2021,
3. P. Tabarisaadi, A. Khosravi, and S. Nahavandi, Comput. "Uncertainty-aware skin cancer detection: The element of doubt," Biol. Med., vol. 144, p. 105357, May 2022.
4. T. Saba, "Handcrafted and non-handcrafted features in computer vision for microscopic skin cancer diagnosis," Microsc. Res. Tech., vol. 84, no. 6, pp. 1272–1283, Jun. 2021.
5. M. S. Ali, M. S. Miah, J. Haque, M. M. Rahman, and M. K. Islam, "An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models," Machine Learning with Applications, vol. 5, p. 100036, Sep. 2021.
6. H. Nahata and S. P. Singh,V. Jain and J. M. Chatterjee, "Deep Learning Solutions for Skin Cancer Detection and Diagnosis," eds., Machine Learning and Healthcare: Machine Learning and Healthcare, Cham: Springer International Publishing, 2020, pp. 159–182.
7. S. Sharma, K. Guleria, S. Tiwari, and S. Kumar, "A deep learning based convolutional neural network model with VGG16 feature extractor for the detection of Alzheimer Disease using MRI scans," Measurement: Sensors, vol. 24, p. 100506, Dec. 2022
8. K. Guleria, S. Sharma, S. Kumar, and S. Tiwari, "Predictive machine learning and deep learning for early hypothyroidism and multiclass classification," Measurement: Sensors, vol. 24, p. 100482, Dec. 2022.
9. S. Sharma, A. Kataria, and J. K. Sandhu, "Applications, Tools and Technologies of Robotic Process Automation in Various Industries,"In 2022 International Conference on Decision Aid Sciences and Applications (DASA), March 1067– 1072, pp. 1067–1072.
10. S. Singh, K. R. Ramkumar, and A. Kukkar, "Machine Learning Techniques and Implementation of Different ML Algorithms," in 2021 2nd Global Conference for Advancement in Technology (GCAT), Oct. 2021, pp. 1–6.
11. A. Sharma and K. "A framework for hotel inventory control system for online travel agency,"

12. , R. Sharma, V. Kukreja,R. K. Kaushal, A. Bansal, and A. Kaur."Rice Leaf Blight Disease detection using multi-classification deep learning model," 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 2022, pp. 1–5, doi: 10.1109/ICRITO56286.2022.9964644
13. M. Vidya and M. V. Karki, "Skin Cancer Detection using Machine Learning Techniques." In the 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), July 2020, pp. 1–5,
14. M. Nawaz et al., "Deep learning and fuzzy k-means clustering for skin cancer detection from dermoscopic images," Microsc. Res. Tech., vol. 85, no. 1, pp. 339–351, Jan. 2022.
15. M. M. Vijayalakshmi, "Image processing and machine learning approaches for the detection of melanoma skin cancer," International Journal of Trend in Scientific Research and Development (IJTSRD), vol. 3, no. 4, pp. 780–784, 2019.
16. M. Nauta, R. Walsh,Diagnostics (Basel), vol. 12, no. 1, Dec. 2021, doi: 10.3390/diagnostics12010040;
17. A. Dubowski, and C. Seifert, "Uncovering and Correcting Shortcut Learning in Machine Learning Models for Skin Cancer Diagnosis."
18. A. Javaid, M. Sadiq, and F. Akram presented The paper "Skin Cancer Classification Using Image Processing and Machine Learning" at the 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST) in January 2021, pages 439–444
19. M. H. Javid presented "Melanoma Skin Cancer Dataset of 10000 images," 29 March 2022. Reached on November 18, 2022. [Online]. Accessible:
20. A. Keutzer, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and F. N. Iandola, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and...