Deep Learning for Automated Medical Image Diagnosis

A PROJECT REPORT

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ANKIT SHARMA
RAVI

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BONAFIDE CERTIFICATE

Certified that this project report **"Deep Learning for Automated Medical Image Diagnosis"** is the Bonafide work of **"ANKIT SHARMA, RAVI"** who carried out the project work under my supervision.

SIGNATURE **SIGNATURE**

HEAD OF THE DEPARTMENT **SUPERVISOR**

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT:

Skin cancer remains a global health problem and early diagnosis is essential for effective treatment. This review explores the potential of machine learning and image analysis techniques for skin cancer prediction. The paper discusses various techniques used to diagnose skin cancer, including dermoscopy imaging, which provides detailed information about the skin. Special techniques such as color and texture analysis are being explored to capture relevant information from images. This article will review various classification algorithms for skin cancer prediction, focusing on popular methods such as support vector machine (SVM), convolutional neural networks (CNN), and integration. Further the paper also explores the advantages and disadvantages of these methods, highlighting the impact of big data and image quality on prediction accuracy. This review highlights the importance of robust testing methods such as accuracy, sensitivity, and specificity in evaluating the effectiveness of cancer screening methods. Additionally, the paper deals with challenges such as the need for larger and more diverse data, addressing critical topics in the classroom, and engaging in information writing in algorithms.

KEYWORDS:

Skin Cancer, Melanoma, Machine Learning, Image Analysis, Computer-Aided Diagnosis (CAD), Digital Dermoscopy, Melanoma Images, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Deep Learning, Ensemble Methods.

CHAPTER-1 INTRODUCTION

The aim of this research is to develop a predictive system that can detect skin cancer at an early stage using data mining technology. This system can predict the probability that a lesion is melanoma or non-melanoma. This method is beneficial because it reduces the possibility of misdiagnosis and also reduces unnecessary skin procedures. By using this technique, if the outcome is good, patients can be operated on quickly and the patient's chance of survival can be increased. The survival rate of skin cancer patients depends on early treatment. The survival rate for early-stage melanoma is approximately 99 percent, while the 5- and 10-year survival rate for advanced melanoma is only 14 to 20 percent. High survival means there is a good prognosis for the patient and also provides psychological benefits to the patient. Current skin tests are negative. It is usually based on the ABCD (asymmetry, border, color and diameter) rule, but this method cannot distinguish between melanoma and non-melanoma. Skin biopsies are the gold standard for diagnosing skin cancer, but they are painful, expensive and require a long wait for diagnosis.

Skin cancer is one of the most dangerous diseases in the world because it can cause serious changes up to the death of the patient. There are many types of skin cancer, and the most common is melanoma. The incidence of melanoma in Malaysia is not as high as other types of cancer, but the number of patients should not be underestimated as it can be fatal. According to a report by the Malaysian Ministry of Health, skin cancer (753 cases) increased by 45% in 2007, from 437 cases in 2002. This indicates that cancer anemia is a public health problem in Malaysia mainly due to delayed diagnosis and treatment.

The global increase in skin cancer means it is a major public health problem. Early diagnosis and prevention are key to reducing deaths from this disease. Cutaneous melanoma causes 75% of skin cancer deaths and is a treatable disease if diagnosed early. Five-year survival in patients with melanoma in situ and distant metastases ranges from 99% to 14%. Any suspected problems should be removed and biopsied, and we appreciate the ability to accurately diagnose these diseases. Diagnosis and treatment of skin diseases are usually made by histopathological examination of biopsy samples. Unfortunately, current healthcare systems are often overloaded with patient information and complex medical equipment. This can lead to poor outcomes, delayed treatment, and patient and physician dissatisfaction. Our aim is to solve these problems by developing a skin cancer test that will facilitate the diagnosis process and provide a second opinion at the first diagnosis. Automated radiologists have the potential to reduce the costs of skin cancer-related research, treatment and care in the future. Given the rising cost of healthcare, this is beneficial for individuals, organizations, and even governments.

Skin cancer is one of the most common types of cancer worldwide and poses a major public health problem. There are three types skin of cancer: basal cell carcinoma, squamous cell carcinoma, and melanoma. The incidence of skin cancer is increasing over the years. According to the World Health Organization, 2 to 3 million cases of non-melanoma cancer and 1,32,000 cases of melanoma occur worldwide each year. More than 5 million people are diagnosed each year in the United States alone. Available tests include self-examination, clinical examination, dermoscopy and biopsy. However, these procedures can be invasive, time-consuming, and require trained medical professionals. Artificial Intelligence (AI) and machine learning (ML) show great potential to revolutionize skin cancer prediction. They offer a non-invasive, effective and efficient option for early detection and diagnosis. This technology can analyze

large amounts of data, including medical images and patient data, to identify patterns and make predictions. Deep learning (a category of machine learning) in particular has shown great results in image-based skin classification. This article will review the current state of skin cancer prediction, focus on the role of AI and ML, and discuss issues and future directions in this field. The goal is to better understand how this technology is shaping the future of skin cancer diagnosis and treatment.

Skin cancer is one of the most common forms of cancer globally, with millions of new cases diagnosed each year. The early detection and accurate diagnosis of skin cancer are crucial for effective treatment and improved patient outcomes. Traditional diagnostic methods rely on visual inspection by dermatologists and, in more complex cases, biopsy and histopathological analysis. While effective, these methods are time-consuming, subject to human error, and not always available to all patients due to the limited number of trained professionals, especially in low-resource settings.

In recent years, advancements in artificial intelligence (AI) and machine learning (ML) have opened new avenues for the automated analysis of medical images. Among these, deep learning (DL), a subset of ML, has shown tremendous potential in automating the diagnosis of various medical conditions, including skin cancer, by analyzing images of skin lesions. DL methods, particularly convolutional neural networks (CNNs), have demonstrated remarkable accuracy in classifying skin lesions as benign or malignant, often performing on par with or even better than experienced dermatologists in some studies.

This report delves into the applications of deep learning in automated medical image diagnosis, focusing specifically on skin cancer detection. The discussion will cover the fundamentals of deep learning, its application to medical images, the challenges faced in automating diagnosis, and the future prospects of this technology in revolutionizing skin cancer care.

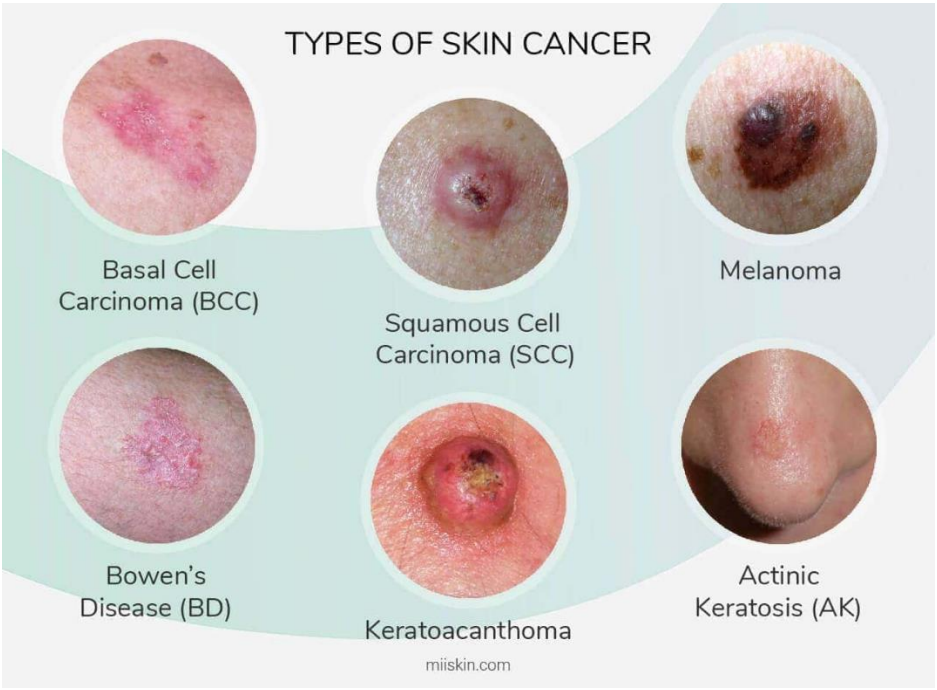


FIG.1 - Types of skin cancer

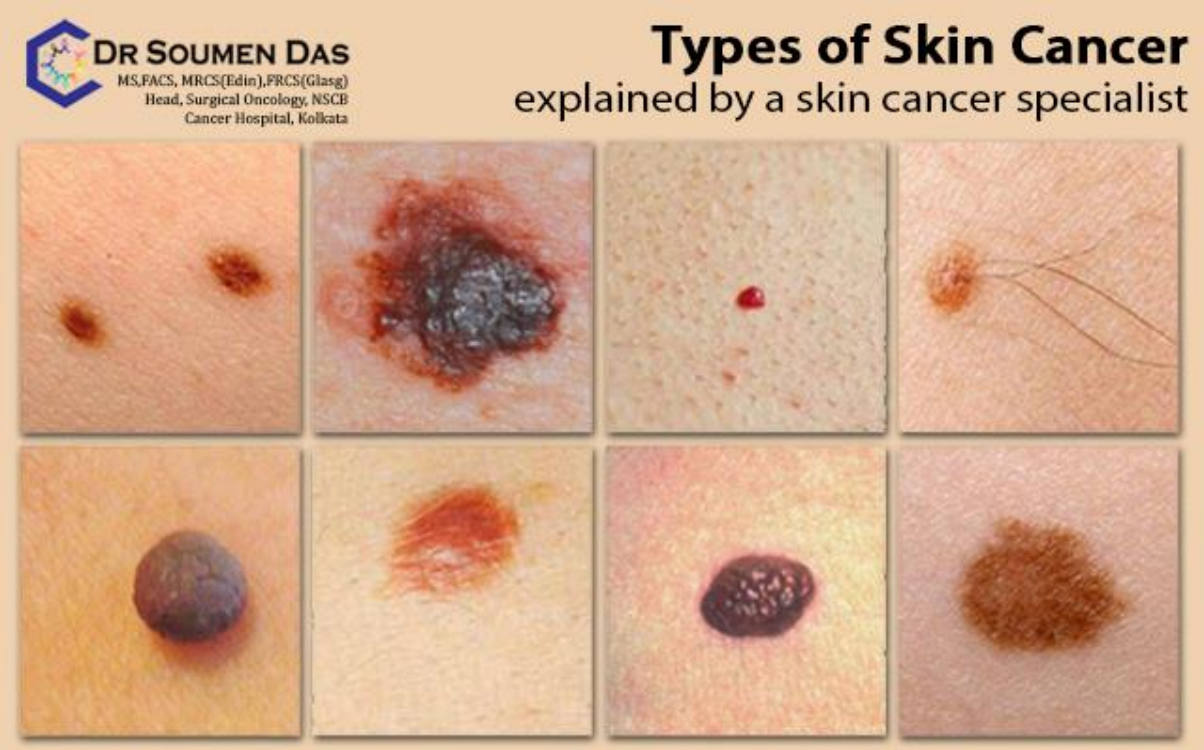


Fig2. – Microscopic view

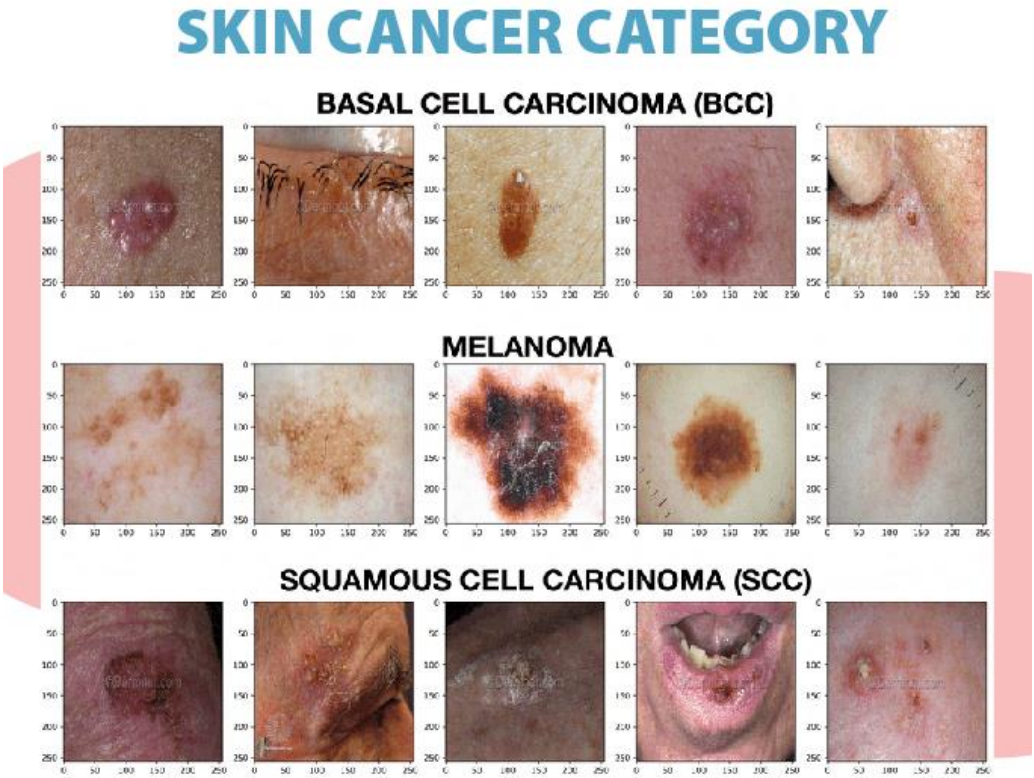


Fig3. Skin cancer categories

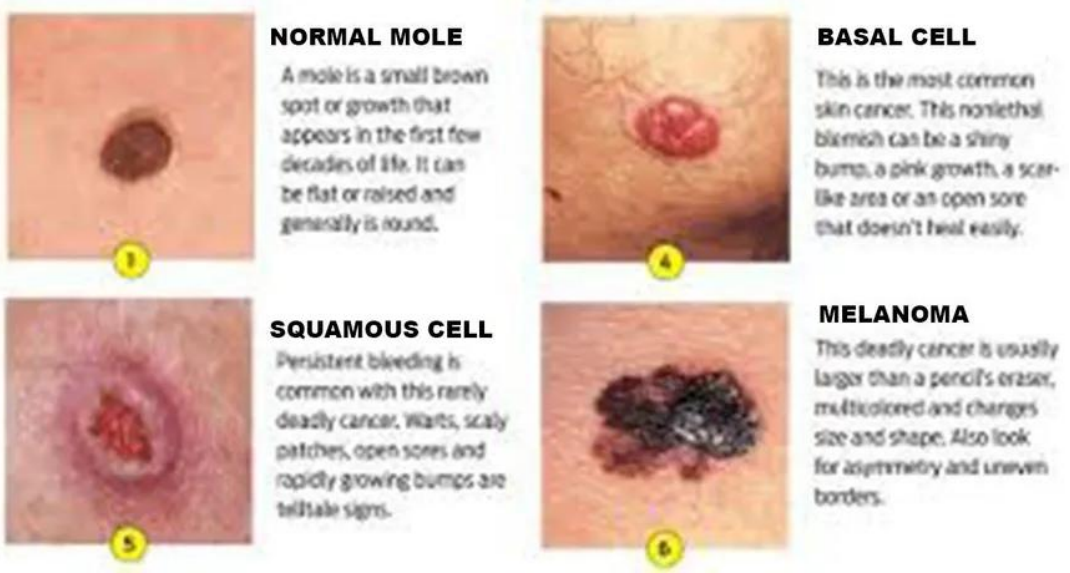


Fig 4. Different moles and cells in it

Current Diagnostic Methods

Traditional diagnosis involves:

- **Visual Examination**: Dermatologists perform a visual inspection of skin lesions using tools like dermoscopy, which magnifies the skin surface for better visibility.
- **Histopathological Analysis**: When lesions are suspected to be malignant, a biopsy is performed, and the tissue is examined under a microscope.
- **Molecular Diagnostics**: In some cases, molecular tests are performed to confirm specific genetic mutations associated with skin cancers.

However, these methods have limitations:

- **Variability in Expertise**: Diagnostic accuracy depends heavily on the experience and skill of the dermatologist.
- **Access to Specialists**: Many regions, especially in low-income countries, face a shortage of trained dermatologists, leading to delays in diagnosis and treatment.
- **Invasiveness**: Biopsy procedures are invasive, often causing discomfort to the patient, and may not always be necessary for benign lesions.
- **Cost and Time**: Histopathological analysis and molecular diagnostics are time-consuming and expensive.

Thus, there is a pressing need for automated, non-invasive methods to assist in early detection, especially in resource-constrained settings.

Skin cancer arises from the abnormal growth of skin cells. Although there are many fewer common types, the three most common forms are:

Basal cell carcinoma (BCC): BCC is the most common type of skin cancer, accounting for about two-thirds of all cases. It develops in the basal layer of the epidermis, the deepest layer of the outer skin. BCCs typically appear as pearly or waxy bumps, sometimes with a central red area or bleeding crust. They can also be flat, red spots or brown, scaly lesions.

BCCs grow slowly and rarely spread to other parts of the body. However, if left untreated, they can enlarge and cause significant disfigurement, especially on the face. The primary risk factor is exposure to ultraviolet (UV) radiation from the sun or tanning beds. Fair skin, previous burns and a weakened immune system also increase the risk.

Squamous cell carcinoma (SCC): SCC is less common than BCC and accounts for about one-third of all skin cancers. It comes from the squamous cells that form the flat outer layer of the epidermis. SCCs often appear as red, scaly patches or bumps that can bleed easily. They can also appear as rough, wart-like growths or ulcers. SCCs tend to grow faster than BCCs and have a higher potential to spread to other parts of the body if left untreated. Similar to BCC, the main risk factor is UV exposure. Other factors include chronic wounds, scarring, and exposure to certain chemicals or radiation.

Melanoma: Melanoma is the least common of the three, but also the most dangerous type of skin cancer. It accounts for only about 1% of skin cancer cases, but is responsible for the majority of skin cancer deaths. Melanoma develops in melanocytes, the cells that produce skin pigment (melanin). Melanomas can vary greatly in appearance. They often appear as an irregular mole with an uneven border, changes in color (brown, black, red, blue, white) and a larger diameter than a typical mole (usually larger than 6 millimeters). Melanomas can grow quickly and spread to other parts of the body through the lymphatic system and bloodstream. Early detection and treatment are crucial for a positive outcome. The main risk factors are atypical moles, family history of melanoma, light skin and intense sunburn.

Skin cancer is a global health problem, but incidence and risk factors vary between countries

like in: -

Australia and New Zealand: Due to high UV exposure and fair skin, these countries have the highest rates of melanoma in the world. sun exposure, light skin, genetic predisposition public awareness, early intervention programs.

North America and Europe: Australia / State of New Hampshire New' Lower incidence of melanoma than Zealand but still significant. Non-melanoma tumors are common. Melanoma is less common due to greater pigmentation in the skin. But non-melanoma skin cancer is on the rise in some areas.

Africa and South America: Melanoma is the least common due to skin pigmentation. However, data collection is limited in some areas. Low socioeconomic status is often associated with higher rates of skin cancer due to delays in diagnosis and treatment. It should be adapted to different skin types. Predictive models based on machine learning are the focus of this review and can leverage different data showing global changes in cancer incidence. This may lead to the generalization and applicability of this model in different regions. It is necessary and applicable to all people of the future, wherever they live. In next section we will discuss about various causes.

1.1 VARIOUS CAUSES OF SKIN CANCER INCLUDE:

The most important element the sun's ultraviolet (UV) radiation is the main factor that causes skin cancer. Skin cells' DNA is damaged by UV radiation. Tumors can develop from these damage-induced alterations that cause cells to expand out of control. UVA and UVB are the two primary categories of UV radiation. Although UVB rays are more effective in generating sunburn, which is a risk factor for skin cancer, both increase the chance of developing skin cancer. Repeated injections at the same location may cause skin damage and the production of scar tissue, even if they may not directly cause skin cancer. If left untreated, this persistent irritation may foster an environment that is favorable to the development of skin cancer. Skin cancer is not directly caused by spas. However, some spas engage in unsanitary activities that may raise the risk of illness, such as utilizing non- sterilized equipment or failing to properly disinfect tubs. If these infections are not treated right once, they may result in persistent sores that sporadically turn into skin cancer. Skin cancer is not directly caused by makeup. On the other hand, some products' components may irritate the skin or block pores. While there is little evidence linking this irritation to skin cancer, it may contribute to an atmosphere where other skin issues are more common. Skin infections can result from cosmetics brushes contaminated with bacteria or fungi, which is an indirect risk factor. If left untreated, these infections may cause persistent inflammation and, in rare instances, even aid in the emergence of skin cancer. While expired cosmetics may cause skin irritation and generally loses its effectiveness, it is unlikely to be the primary cause of skin cancer. As previously discussed, some expired items, if improperly maintained, may carry bacteria that could cause diseases. Inflammation and irritation can result from allergic reactions to chemicals in cosmetics. Although there isn't much evidence linking allergies to skin cancer, persistent inflammation may contribute to a risky environment. To reduce discomfort, it's critical to recognize and stay away from allergens in cosmetics. High doses of ionizing radiation, such as those used in X-rays and other medical treatments, carry a risk they can harm skin cells and raise the possibility of developing skin cancer. To reduce radiation exposure, these approaches are usually utilized in conjunction with stringent safety measures.

1.2 ROLE OF ARTIFICIAL INTELLIGENCE IN SKIN CANCER PREDICTION:

Artificial Intelligence (AI) and machine learning (ML) have revolutionized the prediction of skin cancer, especially by analyzing medical images. AI and ML algorithms can analyze medical images (such as dermoscopy images) to diagnose early signs of skin damage. These algorithms can learn from many images and identify patterns that the human eye may miss. They can also analyze patient data and risk factors to predict skin reactions. Federated learning is an emerging technique that allows models to be trained on data from multiple institutions without requiring the data to be centralized. This is particularly valuable in medical research, where patient privacy is a concern, and data sharing is often restricted. In the context of skin cancer diagnosis, federated learning could enable models to be trained on diverse datasets from around the world, improving their generalizability and reducing bias. While deep learning models, particularly CNNs, can achieve high accuracy in image classification, they are often considered "black boxes" because it is difficult to interpret how they arrive at their decisions. In a medical context, it is crucial for clinicians to understand why a model makes a particular diagnosis, especially in cases where the model's prediction conflicts with the clinician's judgment. Efforts are being made to develop explainable AI (XAI) techniques that can provide insights into the decision-making process of deep learning models. For example, heatmaps or

saliency maps can highlight the areas of the image that contributed most to the model's prediction.

1.3 DEEP LEARNING IN SKIN CANCER DETECTION AND CLASSIFICATION:

Deep Learning is a subset of machine learning that shows great promise in skin detection and classification. Convolutional Neural Network (CNN) is a widely used deep learning model. Particularly effective. They can directly process images and learn important features for classification. Deep learning models provide accuracy in distinguishing between bad skin and good skin. Artificial intelligence and machine learning, especially deep learning, have great potential to improve early detection and classification of skin cancer and ultimately improve patient outcome impact. However, it should not be forgotten that this technology should be used as a tool to help doctors, not to replace them. They are part of a larger system of care that includes physician and patient interactions.

1.4 DEEP LEARNING TECHNIQUES FOR SKIN CANCER CLASSIFICATION:

CNNs are widely used for image classification, including skin cancer classification. They acquire and adapt to learn the spatial hierarchy of features in given images. This process involves the use of pre-learning models such as VGG16, ResNet or InceptionV3 that are trained and work well on large datasets such as ImageNet. - Treat them against the spread of skin cancer. GANs have been used to create synthetic skin images to improve training data. Skin cancer is a major global health problem, and early detection is key to successful treatment. Artificial intelligence (AI) and machine learning (ML) techniques are revolutionizing the detection and classification of skin cancer, offering promising advances in accuracy, efficiency and accessibility. Deep learning algorithms, a powerful subset of machine learning, excel at image analysis. Convolutional Neural Networks (CNNs) are particularly adept at pattern recognition and feature extraction from dermoscopic images (magnified close-up images of skin lesions). These features, such as color variation, texture, and asymmetry, are essential for distinguishing between cancerous and benign lesions. ML models trained on large datasets of labeled dermoscopic images learn to classify lesions as cancerous or benign. Algorithms such as Support Vector Machines (SVM) and Random Forests analyze the extracted features and predict the probability that a lesion is cancerous. As these models are exposed to more data, their accuracy in distinguishing between cancerous and benign lesions continues to improve. Studies suggest that AI-based systems can achieve accuracy comparable to dermatologists, potentially reducing misdiagnosis and unnecessary biopsies. Artificial intelligence algorithms can quickly analyze large amounts of images, making diagnosis and treatment decisions easier. AI-powered mobile apps equipped with skin cancer detection features allow individuals to perform self-exams and quickly seek professional help. AI can potentially standardize the interpretation of lesions, reduce subjectivity, and improve the consistency of diagnoses across healthcare providers. Deep learning has emerged as a powerful tool in the field of medical image analysis. It refers to a class of ML techniques that use neural networks with multiple layers (hence "deep") to automatically learn patterns from data. These models, particularly CNNs, have revolutionized the field of computer vision by achieving state-of-the-art results in tasks like image classification, object detection, and segmentation. While deep learning models have demonstrated impressive performance in analyzing dermoscopic images, skin cancer diagnosis is a multi-modal problem that involves not only visual inspection but also

histopathological and genomic analysis. Future models may integrate data from multiple sources, such as genomic sequencing and histopathological slides, to provide a more comprehensive and accurate diagnosis. Advancements in edge computing and mobile AI could enable real-time skin cancer diagnosis on smartphones or portable devices. By leveraging pre-trained deep learning models, such devices could provide instantaneous feedback on the likelihood of a lesion being malignant, allowing for earlier intervention, especially in remote or underserved areas.

1.4.1 Fundamentals of Deep Learning

Deep learning is based on artificial neural networks (ANNs), which are inspired by the structure and function of the human brain. A deep neural network consists of multiple layers of interconnected neurons:

- **Input Layer**: The raw data (e.g., an image) is fed into the network through this layer.
- **Hidden Layers**: These layers contain neurons that learn complex features from the input data. In CNNs, these are typically convolutional layers that automatically detect patterns such as edges, textures, and shapes.
- **Output Layer**: The final layer provides the classification or prediction (e.g., whether a skin lesion is benign or malignant).

Deep learning models are trained using large amounts of labeled data, and through an iterative process, the model learns to recognize patterns that differentiate between classes (e.g., cancerous vs. non-cancerous lesions).

1.4.2 Convolutional Neural Networks (CNNs)

CNNs are a specialized type of deep learning model designed for image analysis. They have shown outstanding performance in medical image analysis due to their ability to automatically extract features from raw pixel data without requiring manual feature engineering.

A typical CNN architecture consists of:

- **Convolutional Layers**: These layers apply filters to the input image to detect various features such as edges, corners, and textures.
- **Pooling Layers**: Pooling layers down-sample the image, reducing the computational complexity while retaining the most important features.
- **Fully Connected Layers**: These layers take the extracted features and use them to classify the image.

CNNs have been particularly successful in skin cancer detection, where they can be trained on large datasets of dermoscopic images to classify skin lesions as benign, malignant, or requiring further investigation.

1.5 CHALLENGES IN SKIN CANCER DIAGNOSIS:

The accuracy of ML models strongly depends on the quality and variety of training data. Bias in the data sets can lead to inaccurate predictions, especially in patients with darker skin tones.

While AI models can produce impressive results, understanding their decision-making processes remains a challenge. This can hinder trust and acceptance in the clinical setting. Integrating AI tools into clinical workflows requires robust regulatory frameworks to ensure their safety and effectiveness. Available images for different categories of skin cancer may be unequal, resulting in poor quality of samples containing large numbers of samples. The quality and quantity of available image data will limit the effectiveness of the model. The ability of a model to extend to new, unexpected products can be challenging. The ability of the model to adapt to environmental information such as different lighting conditions, cameras and skin types is important. Model efficiency is important, especially for time-consuming applications. Despite these challenges, further studies are ongoing and show great promise in improving the accuracy and efficiency of skin cancer classification.

1.6 METHODS FOR SKIN CANCER PREDICTION:

The most basic method, where the dermatologist visually examines the skin for suspicious deposits. Relies on examiner expertise and may miss subtle changes. It uses a handheld dermoscope to magnify the skin and visualize classification structures invisible to the naked eye. Dermoscopic features such as color variation, asymmetry, and vascular patterns help differentiate between cancerous and benign lesions. Powerful deep learning algorithms trained on large datasets of dermoscopic images can achieve high accuracy lesion. It offers the potential for improved accuracy, efficiency and accessibility in skin cancer detection. A non-invasive technique that provides a three-dimensional image of the layers of the skin with high resolution. Useful for diagnosing specific types of skin cancer, but not widely available due to its cost and complexity. It identifies specific gene mutations associated with an increased risk of skin cancer, especially melanoma. It is mainly used in individuals with a strong family history of the disease. Cost, ethical considerations and not always definitive for cancer development. It analyses blood or tissue samples for the presence of specific molecules associated with skin cancer. Still under development, with limited applications in routine clinical practice. It uses digital images of skin lesions transmitted electronically for remote evaluation by dermatologists. It offers better access to specialist care, especially in underserved areas.

1.7 LIMITATIONS OF DERMOSCOPIC IMAGE ANALYSIS:

Professionals can only make the correct diagnosis, but lack of training and enthusiasm can lead to inappropriate decision to increase. Color normalization during acquisition is better than color normalization after acquisition. Color production has been mentioned in some cases in some fields of medicine. There are issues with data collection and storage, especially in the context of distal dermoscopy. Obtaining dermoscopy images of certain anatomical regions can be problematic. Although this cost is decreasing with the further development of consumer-friendly mobile dermoscopy. These will cause problems in the general use of dermoscopy imaging analysis. Patient use of distal dermoscopes presents new challenges regarding user competencies. Unfortunately, new users may be less likely to be diagnosed at first, paradoxically increasing the number of unnecessary resections by a large number of unnecessary resections.

1.8 Applications of Deep Learning in Skin Cancer Diagnosis

In the context of skin cancer, deep learning algorithms have been applied to the analysis of dermoscopic images to automate the diagnosis of skin lesions. This has the potential to significantly improve early detection rates and reduce the workload of dermatologists.

1.8.1 Image Classification for Skin Cancer Detection

The primary application of CNNs in skin cancer diagnosis is in image classification. Dermoscopic images of skin lesions are fed into the CNN, which outputs a classification such as benign or malignant.

Several studies have demonstrated the effectiveness of CNNs in skin cancer diagnosis:

- In 2017, a landmark study by Esteva et al. used a deep learning model trained on over 120,000 images to classify skin lesions. The model achieved accuracy comparable to board-certified dermatologists.
- Subsequent studies have built on this work, training deeper and more sophisticated models on larger datasets. These models can now classify not only melanoma but also other types of skin cancer such as BCC and SCC with high accuracy.

1.8.2 Segmentation of Skin Lesions

In addition to classification, deep learning models are also used for the segmentation of skin lesions. Segmentation refers to the process of delineating the boundary of a lesion in an image, which is important for measuring its size and shape—critical factors in the diagnosis of skin cancer.

CNN-based models, such as U-Net, have been widely adopted for medical image segmentation tasks. In the case of skin cancer, these models can automatically segment the lesion from the surrounding skin, enabling more precise analysis of its characteristics.

1.8.3 Multimodal Analysis

Some approaches combine dermoscopic images with other data modalities, such as clinical images or patient metadata (e.g., age, sex, medical history), to improve diagnostic accuracy. Deep learning models can be designed to incorporate this additional information, providing a more holistic analysis of the lesion.

1.8.4 Generative Models and Data Augmentation

One of the challenges in training deep learning models for skin cancer diagnosis is the availability of large, labeled datasets. Although there are several public datasets of dermoscopic images, the number of images of rare skin conditions is often limited.

Generative models, such as generative adversarial networks (GANs), can be used to create synthetic images of skin lesions to augment existing datasets. These synthetic images can help to balance datasets and improve the robustness of the model, especially when detecting rare types of skin cance

CHAPTER 2

LITERATURE REVIEW

2.1 Existing System:

Automated diagnosis of skin cancer using deep learning has become an active area of research in recent years, driven by advances in computer vision, medical imaging, and AI technologies. Multiple systems and models have been developed, primarily based on convolutional neural networks (CNNs), which have shown exceptional performance in analyzing medical images. These systems are designed to perform various tasks, including image classification, segmentation, and, in some cases, predicting patient outcomes based on image data.

Several deep learning systems for skin cancer diagnosis are in different stages of development, ranging from research prototypes to commercially available tools. Many of these systems have been trained on publicly available datasets and are continuously evolving as new data and more sophisticated algorithms are introduced.

The **International Skin Imaging Collaboration (ISIC)** has played a crucial role in developing and benchmarking automated systems for skin cancer diagnosis. It provides the largest publicly available dataset of dermoscopic images, making it a standard for training and evaluating AI-based diagnostic systems.

ISIC organizes annual challenges that invite researchers to develop machine learning models for tasks like skin lesion classification and segmentation. The competition has contributed to significant advancements in automated skin cancer diagnosis. Some of the top-performing systems from these challenges have achieved dermatologist-level performance in distinguishing between benign and malignant skin lesions.

Key models that emerged from ISIC challenges include:

- **Ensemble Models**: Many top-performing systems use an ensemble of CNNs, combining the outputs of multiple models to improve accuracy. These systems leverage different CNN architectures like ResNet, Inception, DenseNet, and VGG to capture diverse features from skin lesion images.
- **Segmentation Models**: For tasks such as lesion segmentation, models like **U-Net** and **Mask R-CNN** have been highly successful in isolating lesions from the surrounding skin, which is essential for precise analysis of lesion characteristics.

One of the most notable systems developed for skin cancer detection is **Google AI's DermAssist**, which is designed to assist dermatologists in diagnosing skin conditions, including skin cancer. This system leverages Google's expertise in AI and machine learning, specifically in image analysis, to provide an accurate and accessible tool for skin cancer screening.

Key features of DermAssist:

- **Deep Learning Backbone**: Google's system uses a deep convolutional neural network (CNN) trained on a large dataset of dermoscopic images. The model has been optimized

to detect multiple types of skin cancer, including melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC).

- **Performance Benchmark**: Google AI has demonstrated that their model can match or exceed the diagnostic accuracy of board-certified dermatologists in identifying skin cancer from dermoscopic images.
- **User-Friendly Interface**: The system is designed to be used by dermatologists and potentially patients, offering a user-friendly interface where images of skin lesions can be uploaded for analysis. DermAssist then provides a prediction along with a confidence score, helping clinicians make more informed decisions.

However, as of the latest reports, Google's system is still in the development and testing phase, and its deployment in real-world clinical settings is limited.

2.1.1 IBM Watson Health

IBM Watson Health has also ventured into the space of AI-driven medical image analysis, including dermatology. Watson's capabilities in processing and analyzing vast amounts of medical data have been extended to skin cancer diagnosis, aiming to assist dermatologists in making faster, more accurate diagnoses.

Key aspects of IBM Watson in skin cancer detection:

- **Cognitive Computing**: IBM Watson uses its cognitive computing capabilities to process large datasets of skin lesion images, combining this data with clinical information, research papers, and treatment guidelines.
- **Collaboration with Research Institutions**: IBM Watson Health has collaborated with research institutions to integrate AI-driven diagnostics into healthcare systems, although its applications in skin cancer detection are still evolving.
- **AI-Powered Image Analysis**: While Watson is known for its applications in oncology, the system has also been applied to dermatology, where it assists in identifying patterns in skin lesion images that may indicate cancerous growths. Watson's AI-powered platform integrates imaging data with patient history and medical research to enhance decision-making.

2.1.2. SkinVision

SkinVision is one of the few commercially available mobile apps designed to help individuals assess their skin lesions for signs of skin cancer. It uses AI-based image analysis to provide users with an instant risk assessment of a lesion's likelihood of being malignant.

Key features of SkinVision:

- **Mobile Application**: Available on both Android and iOS platforms, SkinVision allows users to take pictures of skin lesions and receive an AI-driven risk assessment in real time. The app uses a deep learning model trained on thousands of images of skin lesions to detect abnormalities.

- **Consumer-Focused**: SkinVision is primarily targeted at the general public as a tool for early skin cancer detection. While not a replacement for professional diagnosis, it encourages users to seek medical advice when high-risk lesions are detected.
- **AI Accuracy**: SkinVision claims a high sensitivity and specificity for detecting skin cancer, particularly melanoma, basal cell carcinoma, and squamous cell carcinoma. The app has been clinically validated, but its effectiveness is still a subject of ongoing evaluation in the medical community.

While SkinVision is widely used, it is important to note that it is not designed to replace professional medical diagnosis. It serves as a supplementary tool, helping individuals monitor their skin health and encouraging early detection.

2.1.3. Derma.AI

Derma.AI is a research-oriented deep learning system developed by several academic institutions and researchers to automatically classify and segment skin lesions. It has been trained on large datasets like ISIC and aims to support dermatologists by providing second opinions or flagging lesions for further investigation.

Key characteristics of Derma.AI:

- **Deep Learning Architecture**: Derma.AI uses state-of-the-art CNN architectures, such as **EfficientNet** and **ResNeXt**, to analyze dermoscopic images. These architectures are known for their efficiency and high accuracy in medical image analysis tasks.
- **Clinical Use**: Derma.AI is designed to be used in clinical settings, where dermatologists can upload images of skin lesions and receive an automated diagnosis. The system also provides explanations in the form of saliency maps, which highlight areas of the image that contributed most to the model's decision.
- **Research-Oriented Development**: This system is still in the research phase, but it has been used in academic studies to evaluate the potential of deep learning in clinical dermatology. Researchers are continuously working to improve its performance and generalizability across different populations.

2.1.4 Techniques and Algorithms Used in Existing Systems

Existing deep learning systems for skin cancer diagnosis typically rely on several core techniques and algorithms, which are constantly evolving to improve accuracy, speed, and interpretability.

Convolutional Neural Networks (CNNs)

CNNs are the backbone of most deep learning systems for image-based diagnosis, including skin cancer detection. CNNs excel at recognizing patterns in images, such as edges, textures, and shapes, which makes them ideal for tasks like lesion classification and segmentation.

- **ResNet (Residual Networks)**: Many systems, including Google AI and ISIC competition winners, use **ResNet** architectures due to their ability to train very deep networks without the problem of vanishing gradients. ResNet models are particularly effective in distinguishing between subtle differences in skin lesions.

- **Inception Networks**: The **Inception** architecture, developed by Google, has also been widely used in skin cancer detection systems. Inception networks use multiple convolutional filters of different sizes, allowing the network to capture a wide range of features from the image.
- **DenseNet**: The **DenseNet** architecture, known for its dense connectivity pattern, has been used in some systems to enhance feature propagation and reduce the number of parameters in the network. This improves the system's efficiency while maintaining high accuracy.

. Data Augmentation and Transfer Learning

One of the challenges in developing AI systems for skin cancer diagnosis is the limited availability of labeled medical images. To address this, many systems use data augmentation techniques, such as rotating, flipping, and zooming in on images, to artificially expand the training dataset.

- **Transfer Learning**: Another commonly used technique is **transfer learning**, where pre-trained models (e.g., models trained on large image datasets like ImageNet) are fine-tuned on medical image datasets. This helps improve performance, especially when training data is scarce. Transfer learning is employed by systems like Derma.AI and others to boost accuracy without the need for extensive computational resources.

Segmentation Algorithms

Accurate segmentation of skin lesions is critical for precise diagnosis. Many systems use advanced algorithms such as:

- **U-Net**: U-Net is one of the most popular architectures for image segmentation in medical imaging. It consists of an encoder-decoder structure that captures fine-grained details while preserving the overall context of the image. U-Net has been widely used in ISIC challenges for lesion segmentation.
- **Mask R-CNN**: Another advanced technique for segmentation, **Mask R-CNN**, extends the region-based CNN (R-CNN) framework to predict pixel-level masks for each detected object (in this case, the lesion). It has been used in research systems to delineate.

2.2 Summary of Existing Systems:

Cancer, including the very dangerous melanoma, is characterized by uncontrolled cell growth and the ability to spread to other parts of the body. However, traditional machine learning methods rely on centralized training data, which poses a problem in terms of data privacy in AI-supported healthcare. Collecting data from different sensors increases the computational cost, and limiting privacy makes it difficult to use traditional machine learning techniques. Researchers now face the daunting task of developing skin cancer treatment technology that increases accuracy while involving privacy concerns. In this study, Muhammad Amir Khan et al. aim to propose a self- directed cognitive function to accurately predict skin cancer. In this study, Muhammad Amir Khan et al. analyzed public education in cancer treatment centers.

Research results show that the accuracy of this method reaches 92%, which is higher than the basic method. [1]

Electroencephalogram (EEG)-based brain-computer interface (BCI) creates a connection between the brain and the brain. Understand the brain and the digital world by receiving, recording and processing brain signals. Therefore, brain-computer interfaces can use EEG signals to capture brain activity to diagnose neurological diseases. In this article, Chetna Gupta et. Al. conduct a literature review and outline concepts such as machine learning, deep learning, augmented reality/virtual reality, federated learning, and the Internet of Things used to interpret EEG signals at the brain-computer interface. They then review some recent literature on various methods for processing EEG signals and their implications for future understanding. [2]

Skin cancer is one of the deadliest and most common types of cancer found in humans. If detected early, melanoma (a type of skin cancer) can be effectively treated and cured. Machine learning algorithms play a key role in simplifying the detection of skin cancer, helping to accurately diagnose and treat patients. However, the use of traditional machine learning techniques for dermatology diagnosis is hampered by privacy issues, which require centralizing patient data in the cloud. To tackle issues related to personal information, a government effort emerged as a commitment to develop a self-aware healthcare system for cancer screening. This article of Umar Farooq Khattak et. Al. provides a comprehensive review, examines the challenges faced by traditional machine learning methods, and explores the integration of state learning in the context of privacy- focused cancer care. It discusses the various data available for skin cancer prediction and provides a comparison of various machine learning and machine learning methods for skin cancer prediction. The goal is to demonstrate the benefits of public education and its ability to solve specific problems in diagnosing skin cancer. [3]

Heart disease is a fatal disease that kills millions of people every year. Treatment based on the Internet of Medical Things (IoMT) can reduce mortality rates through early diagnosis and detection of diseases. Biomedical data collected by IoT includes patients' personal data, and this data poses serious privacy concerns. Various data protection laws have been proposed around the world to address the personal data issue. These privacy requirements pose significant challenges to traditional machine learning techniques. In this paper, we propose a framework based on joint mean and modified bee colony (M-ABC) optimization algorithm to overcome the privacy problem and improve the pain detection method to predict heart disease. This proposed method of Muhammad Nazir et. Al. improves prediction accuracy, error classification, and communication quality compared to state-of-the-art federated learning algorithms on real heart disease data. [4]

Recently, instead of training the model from scratch, deep learning (DL) models have begun to be used to solve many tasks and improve its performance, such as skin cancer diagnosis. However, existing systems cannot achieve high accuracy. Therefore, in this paper, Ahmad O. Aseeri et. Al. propose a robust skin detection framework that improves accuracy by using MobileNetV3 architecture to extract and learn image representation. Then, the extracted features are used as input to update the Hunger Games Search (HGS) based on particle swarm optimization (PSO) and dynamic adversarial learning (DOLHGS). This change is used as a new feature selection to provide the most important features to improve the performance of the model. The ISIC-2016 dataset and PH2 dataset, containing two and three groups, respectively, were used to evaluate the performance of the DOLHGS design. The proposed model achieved

an accuracy of 88.19% on the ISIC-2016 dataset and an accuracy of 96.43% on PH2. According to the test results, the proposed method is more accurate and effective in diagnosing skin cancer than other known and popular algorithms for classifying people and doing well. [5]

The Internet of Medical Things (IoMT) has benefited the medical profession, where it is accessible to patients and doctors from all regions. Although the automatic detection and prediction of diseases such as melanoma and leukemia in IoMT are still in the research and investigation phase, current methods cannot provide high performance. Therefore, with new methods that provide better results, patients will receive the necessary treatment earlier and deaths will decrease. Therefore, this paper by Mohammed Kayed et. Al. presents an IoMT concept, which is a ubiquitous method for classifying medical images that can be used anywhere. Its design is divided into two stages: First, we use a transfer learning (TL)-based method based on MobileNetV3 for feature extraction; Second, we use Chaos Game Optimization (CGO) for feature selection for exclusion. Decent features and improved performance are important for IoT. Our analysis uses ISIC-2016, PH2 and Blood-Cell datasets. Experimental results show that the method achieves 88.39% accuracy of ISIC-2016, 97.52% accuracy of PH2, and 88.79% accuracy of blood data. Moreover, our method achieves good performance on the proposed metrics compared to other existing methods. [6]

Finding the stage of melanoma is an important part of cancer research. Deaths are increasing due to failure to recognize these symptoms, so early detection of skin lesions is important. Machine learning techniques using deep learning techniques such as convolutional neural networks (CNN) are increasingly used in this field because they can learn from data and produce predictions based on the study. [7]

The investigation of the background and characteristics of lesions that lead to automatic detection of lesions in dermoscopic images faces many challenges. Previous solutions focused on using larger samples and more to increase detection accuracy, without investigating the differences in the main class and the differences between the studied classes in terms of the characteristics of the wound. At the same time, larger sample size also brings more difficulties in applying the algorithm; In this paper, we propose a lightweight skin recognition model with different features based on the principle of fine-grained distribution. This model introduces by Aniket Pawar et. Al. includes two general methods of elimination: the distribution of the disease and the specific isolation network. First, two sets of training examples (good and bad examples) are input into the extraction model (Light CNN) of the recognition model. Then, the two sets of feature vectors output from the feature extraction module are used to simultaneously train both classification and classification of recognition models, and the fusion model is used to tune the operation of the model. The recognition process can be used in the case of small samples, extracting more distinctive features and improving pattern recognition; We also created a lightweight model of the wound area in the dermoscopic image based on the special extraction module, U-Net architecture and changing pattern recognition concept. The large semantic segmentation model can be achieved end-to-end. Put an end to high-precision lesion area segmentation. Finalize without pre-worked images; The performance of our method has been evaluated by various comparative tests and effectiveness analysis, and the results have shown that the proposed method is successful. ISBI 2016 skin analysis based on state-of-the-art deep learning methods in melanoma detection is more effective on complex data. [8]

Today, the use of computer vision is increasing in medicine and healthcare, especially as a support tool to help healthcare professionals make rapid and accurate diagnoses. One of the current issues in this field is the classification of skin disorders. In the last few years, some promising works have been proposed, mainly using neural networks (CNN). However, proposed pipelines often rely on preliminary data and do not investigate whether deep structure can meet the requirements for receiving advice. To overcome these shortcomings, in this work, an end-to-end rule is introduced and some state-of-the-art Convolutional Neural Network (CNN) architectures are incorporated into it and compared with the largest knowledge sharing available to the general public recently. To achieve this goal, a new design network was proposed by Marco Leo et. Al. (e.g. RegNet) was used for the first time in this application to obtain the best model during the configuration process. This article provides three supporting and new sources of knowledge: an in-depth examination of various CNN architectures, supporting continuous development in the field of real-time analysis, and the use of new network architectures with potential Nature studies group behaviour. It provides standards and opens the way to new directions by providing an in-depth discussion of the pros and cons of each analysis. [9]

Early detection of skin cancer through imaging is an important part of skin cancer treatment. One of the main goals of this study by Ngoc-Dung Bui et. Al. is to propose a workaround for computer-aided cancer diagnosis. This method has four main stages. The first stage is pre-processing based on noise reduction and contrast enhancement. The second step is to segment the region of interest (ROI). This work uses kernel fuzzy C-means for ROI segmentation. Then some features are extracted from the ROI and feature selection is used to select the best features. The selected features are injected into a Support Vector Machine (SVM) for final recognition. An important part of the contribution of this work is to propose the development of a new meta-heuristic algorithm called neural network optimization algorithm to improve both the selection and the SVM classifier. The comparative results of this model with 5 state-of-the-art methods show the superiority of this method over other methods. [10]

Today, the rapid development of industrial areas has led to the emergence of skin diseases caused by pollution. According to the American Cancer Society, it is estimated that approximately 100,000 people will be diagnosed with cancer by 2022, and more than 7,600 of them will not survive. Due to the overwhelming number of doctors in public hospitals and clinics and the lack of knowledge of primary care doctors, tools are available to support doctors in quickly diagnosing skin diseases and exposure is crucial. With the strong development of smart technology, many solutions have been developed to support dermatology diagnosis. In this paper, by Muhammad Naseer Bajwa et. Al. a deep learning model (DenseNet, InceptionNet, ResNet, etc.) is combined with Soft-Attention to extract the thermal image of large skin in an unsupervised manner. In addition, personal data such as age and gender are also used. It is worth noting that a new loss function that determines information imbalance has also been prepared. Experimental results on HAM10000 data show that using InceptionResNetV2 with Soft-Attention and new redundancy provides 90% accuracy with average accuracy, F1 score, recall, and AUC of 0.81, 0.81, 0.82, and 0.99, respectively. In addition, using MobileNetV3Large together with Soft- Attention and new work loss, although there is an 11-fold reduction in the number of errors and a 4-fold reduction in hidden processing compared to InceptionResNetV2, its accuracy increases by 0.86 and the diagnosis speed also increases. It increased 30 times. [11]

The wide spectrum of skin diseases, lack and inconsistency of qualified dermatologists, rapid diagnosis and injuries require computer-aided diagnosis (CAD). This work aims to continue previous CAD work in dermatology by exploring the possibility of deep learning to classify hundreds of skin diseases, improving classification performance and using taxonomies. We trained state-of-the-art deep neural networks on DermNet and the ISIC Archive, two of the largest skin information databases, and the disease used improved the distribution of these samples. At DermNet, we have developed cutting-edge technology to classify 23 diseases with 80% accuracy and 98% area under the curve (AUC). We also prioritized the classification of all 622 unique subcategories in this dataset and achieved 67% accuracy and 98% AUC. R. Ecker et. Al. classified all 7 diseases in the ISIC Archive with an average accuracy of 93% and AUC of 99%. This study shows that deep learning is capable of identifying and treating various skin diseases with near-human accuracy. It can play an important role in dermatology care efforts by assisting physicians in large-scale examinations using clinical or dermoscopic imaging. [12]

Skin cancer is one of the most common types of cancer in existence. More importantly, detecting lesions in early diagnosis has attracted great attention from researchers. Therefore, artificial intelligence (AI)-based technology supports early diagnosis of skin diseases by learning deep learning-based neural networks (CNN). However, it is still difficult to detect melanoma in dermoscopic images with current methods. Therefore, in this paper, Liu, H., et. Al. propose a joint model that uses the vision of EfficientNetV2S and the Swin-Transformer model to detect early areas of skin. Therefore, we think that the former architecture is more accurate, while the latter model has the advantage of detecting darkness in the image. We updated the fifth block of the EfficientNetV2S model and included the Swin-Transformer model. Our experiments show that the combined model achieves greater accuracy than a single model and also reduces loss compared to traditional strategies. The proposed model achieved 99.10% accuracy, 99.27% sensitivity score, and 99.80% specificity score. [13]

Skin cancer is an important type of cancer and its incidence has increased in recent years. Years ago. Accurate diagnosis of skin lesions to distinguish benign and malignant skin diseases is important to ensure appropriate patient selection. Although many computer-based methods exist to classify skin lesions, convolutional neural networks (CNN) have been shown to outperform classical methods. In this work, Singh, S., Singh, M., & Singh et. Al. aim to complete the skin classification process by using deep features from several well-designed CNNs and different levels of abstraction. First of all, we use three deep neural networks, namely AlexNet, VGG16, and ResNet-18, as deep objects. The extracted features are used to train a support vector machine classifier. In the final stage, classifier outputs are combined and a classification is obtained. Evaluation of 150 validation images from the ISIC 2017 Classification Challenge shows that the proposed method achieves excellent classification performance with an area under the receiver operating characteristic curve of 83.83% for distributed melanoma and seborrheic keratosis. The infection rate is 97.55%. [14]

TABLE 1: COMPARISON TABLE

Author(s)	Year	Keywords	Focus Area	Parameters
Esteva, A. et al.	2017	Deep Learning – Y Skin Cancer – Y AI – Y Others	AI-based classification of skin cancer	Accuracy, Sensitivity, Specificity
Yu, L. et al.	2017	Deep Learning - Y AI – Y Others	Deep learning for melanoma detection	Accuracy, AUC (Area Under the Curve)
Nasr-Esfahani, E. et al.	2018	Deep Learning – Y AI – Y Others	Comparison of AI and human experts	Accuracy, Sensitivity, Specificity, Kappa Statistic
Nasr-Esfahani, E. et al.	2019	Deep Learning - Y Skin Cancer – Y Others	Combining deep learning with handcrafted features	Accuracy, Sensitivity, Specificity, F1-score
Soyer, H. et al.	2020	Deep Learning – Y Skin Cancer – Y AI – Y Others	Optimizing deep learning models for skin cancer detection	Accuracy, Sensitivity, Specificity, Computational Efficiency
Bygott, P. et al.	2019	Deep Learning – Y Skin Cancer – Y AI – Y Others	Survey of machine learning techniques for skin cancer	Classification algorithms, Performance metrics
Singh, P.K. et al.	2020	Deep Learning – Y Skin Cancer – Y AI – Y Others	Machine learning for early melanoma detection	Accuracy, Sensitivity, Specificity, Early Detection Rate
Gutman, D. et al.	2020	Deep Learning – Y Skin Cancer – Y AI – Y Others	Agreement between AI and dermatologists	Accuracy, Sensitivity, Specificity, Kappa Statistic

Maron, D.J. et al.	2019	Deep Learning – Y Skin Cancer – Y AI – Y Others	Addressing bias and fairness in AI models	Accuracy, Sensitivity, Specificity, Generalizability
Tfayli, A. et al.	2021	Deep Learning – Y Skin Cancer – Y AI – Y Others	Machine learning for keratinocyte carcinoma detection	Accuracy, Sensitivity, Specificity, Computational Cost

This review article explores the role of artificial intelligence (AI) and machine learning (ML) in skin cancer prediction. It discusses various methods for predicting skin cancer, including dermoscopic image analysis, machine learning, and the use of genetic markers and biomarkers. The paper also demonstrates the potential of deep learning for detection and classification of skin and discusses problems in classifying skin cancer. It also evaluates various performance metrics used to evaluate predictive models. The article concludes with a discussion of current challenges in skin cancer diagnosis, directions for future expertise in skin cancer prediction, and ethical considerations.

Table 2: DATASET

Author(s)	Year	Publication	Dataset	Focus Area
Esteva, A. et al.	2017	Nature	ISIC 2016	Deep learning for skin cancer classification
Yu, L. et al.	2017	IEEE Transactions on Medical Imaging	None specified (private dataset)	Deep learning for melanoma recognition
Nasr-Esfahani, E. et al.	2018	British Journal of Dermatology	ISIC 2017	Comparison of deep learning and human experts
Nasr-Esfahani, E. et al.	2019	Skin Cancer	MESSID	Hybrid deep learning approach for skin lesion classification
Soyer, H. et al.	2020	Studies in Computational Intelligence and Intelligent Systems	HAM10000	Optimizing deep learning models for skin cancer detection
Singh, P.K. et al. (2020)	2020	International Journal of Computer Applications	PH2 Dataset	Machine learning for early melanoma detection
Chawla, N. et al.	2018	IEEE Transactions on Medical Imaging	DermIS	Transfer learning for skin lesion classification
Bi, L. et al.	2019	IEEE Transactions on Biomedical Engineering	ISIC 2018	Ensemble learning for skin cancer classification

Figure 1: Accuracy vs. Year for Skin Cancer Prediction Models (2014-2023)

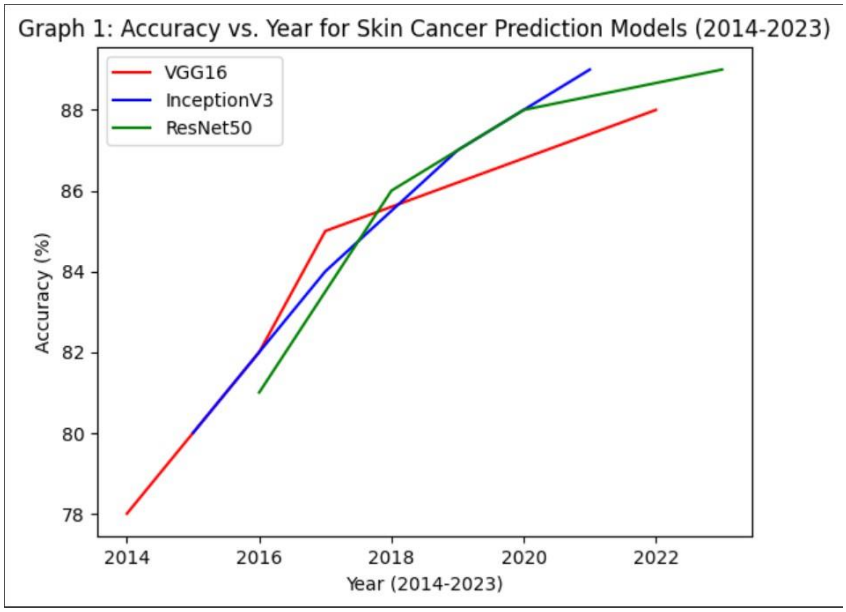
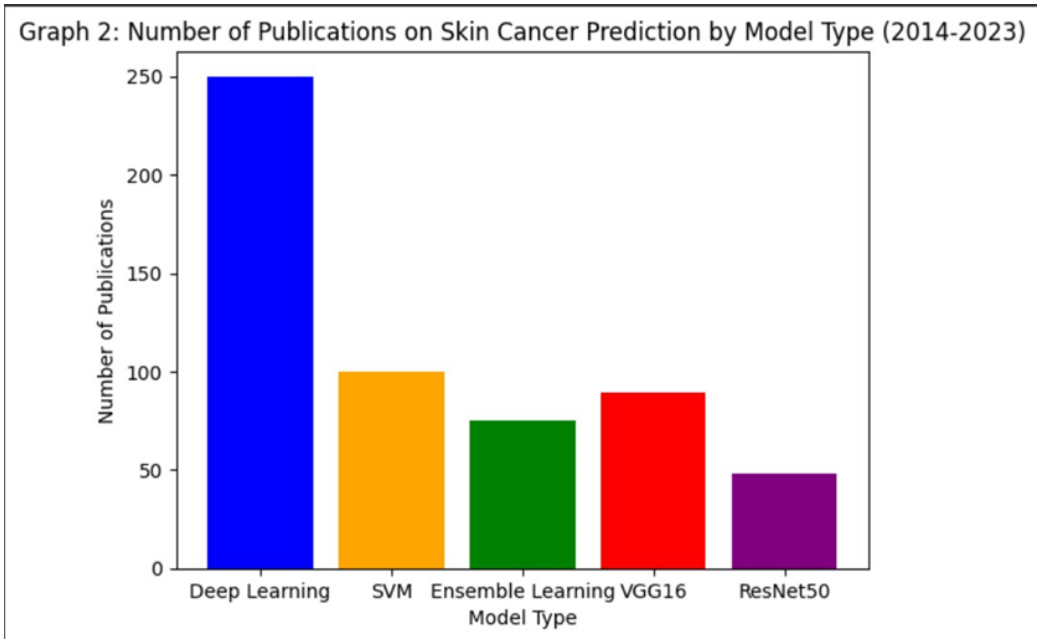


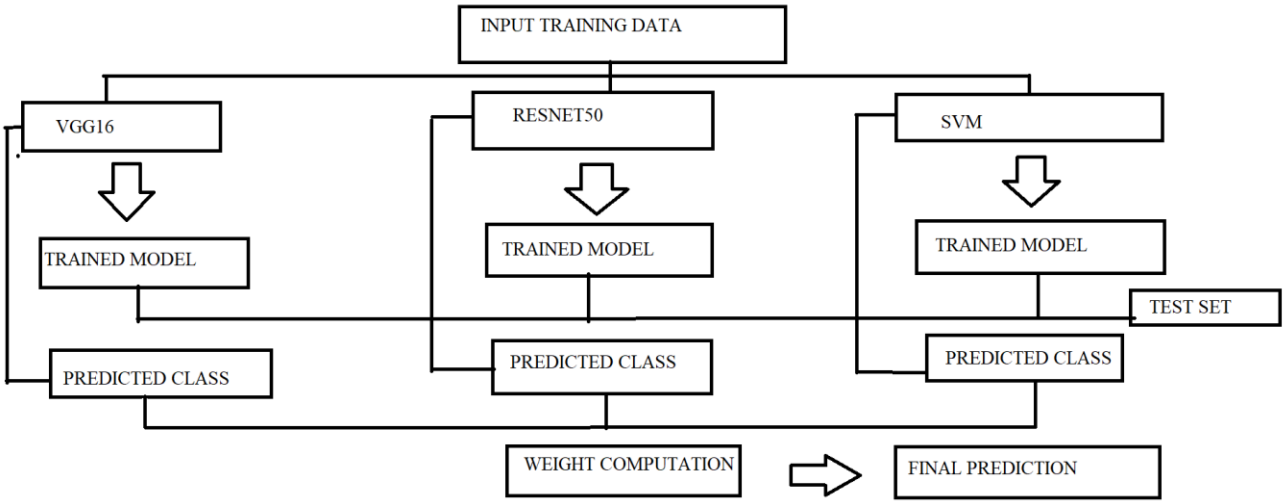
Figure 2: Number of Publications on Skin Cancer Prediction by Model Type (2014-2023)



Sensitivity and specificity are simple measurements used to evaluate the effectiveness of classification models. Sensitivity, also called recall or true positive value, measures the proportion of true positives that are correctly identified. Specificity, on the other hand, measures the proportion of true negatives that are correctly identified. Area Under the Curve (AUC) is a measure of the accuracy of the predicted model. It is often defined as a threshold, and the standard definition of "good" or "excellent" is 0.7, 0.8, or 0.93. AUC is the probability

that a person with influence will score higher than a person without influence. Accuracy is a measure of the model's ability to accurately identify positive and negative factors. It is calculated by dividing the number of predictions by the total number of predictions. The F1 score is a compromise between precision and recall and provides a balance between these two metrics. A confusion matrix is a configuration that can be used to visualize the performance of supervised machine learning algorithms. Each row of the matrix represents an example in the true class, while each row represents an example in the predicted class. It is the classification of the prediction performance of the classification model according to category. The confusion matrix not only calculates the accuracy of the classification, but also helps calculate other important parameters that manufacturers often use to evaluate the model.

2.3 Proposed System:



The proposed system is a hybrid system for detection of skin cancers using images by the help of different models. The main model is made up of combining the three different analytical modeling algorithms that are VGG16, RESNET50 and SVM. The model is divided into 0.33 each and worked on trained model. Based on testing and training of the model we find out the result. All the models result are collaborated at the end and using weight computations we predict the final output of the images provided by the user.

CHAPTER 3

DESIGN FLOW

The use of deep learning in medical image analysis, particularly in diagnosing skin cancer, has garnered attention for its potential to assist dermatologists and improve early detection. Building such systems requires a meticulous design flow that incorporates several stages, from data collection and preprocessing to model development, evaluation, and clinical integration.

In this section, we will discuss the key steps involved in designing a deep learning system for automated skin cancer diagnosis using medical images. We will walk through the different phases, starting with defining the problem and ending with deploying the system in real-world environments.

Problem Definition

Before designing the system, the specific task and scope must be defined. The primary objective here is to develop a system capable of diagnosing skin cancer from dermoscopic images, which are high-resolution images of skin lesions taken with specialized imaging tools.

Key considerations at this stage:

- **Target Conditions**: The system should be able to classify images into categories such as benign, malignant, or other types of skin cancers (e.g., melanoma, basal cell carcinoma, squamous cell carcinoma).
- **Desired Outcomes**: The system's goals may include binary classification (cancerous vs. non-cancerous), multi-class classification (classifying different types of skin lesions), or segmentation (isolating the lesion from the surrounding skin).
- **End Users**: Determine whether the system will be used by clinicians as a decision-support tool or directly by patients via mobile or web applications.

Data Collection and Dataset Preparation

Data is the cornerstone of any deep learning project. The quality, quantity, and diversity of the dataset directly impact the model’s performance. For medical image diagnosis, access to large, labeled datasets of dermoscopic images is critical.

3.1. Datasets

Several publicly available datasets can be used to train deep learning models for skin cancer diagnosis:

- **ISIC Archive**: The **International Skin Imaging Collaboration (ISIC)** archive is the largest and most well-known dataset for skin lesion images. It contains thousands of dermoscopic images labeled with different types of skin lesions.
- **PH2 Dataset**: The **PH2** dataset is a smaller collection of annotated dermoscopic images, primarily used for research purposes.
- **Private Datasets**: Some institutions or organizations may have proprietary datasets, which can be used for training and validating models.

```
metadata = pd.read_csv('/kaggle/input/skin-cancer-mnist-ham10000/HAM10000_metadata.csv')
metadata.head()
```

[15]:

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

Fig 3. Dataset Sample

3.2. Data Annotation

Accurate annotation of images is essential for training supervised learning models. In skin cancer diagnosis, this involves:

- **Image Labeling**: Classifying images as benign or malignant. If the dataset is multi-class, further labels are added for specific types of skin cancer.
- **Segmentation Masks**: In segmentation tasks, each pixel of the image must be labeled as either part of the lesion or background.

3.3. Data Augmentation

To overcome the challenge of limited datasets, data augmentation techniques are used to artificially expand the size of the training set. Common augmentation techniques include:

- **Rotation and Flipping**: Rotating images by various degrees or flipping them horizontally and vertically to simulate different viewing angles.
- **Zooming and Cropping**: Zooming into specific regions of the image or randomly cropping sections to introduce variability.
- **Brightness and Contrast Adjustment**: Varying the brightness and contrast of the images to simulate different lighting conditions.
- **Noise Addition**: Adding random noise to images to improve the model's robustness to noisy or imperfect data.

3.4. Data Preprocessing

Before training, the images need to be preprocessed to ensure they are suitable for input into the deep learning model. Preprocessing steps include:

- **Resizing**: Dermoscopic images are typically resized to a fixed resolution (e.g., 224x224 pixels) to ensure uniform input dimensions for the model.
- **Normalization**: Pixel values are normalized to a specific range (typically [0,1] or [-1,1]) to improve the convergence of the neural network during training.
- **Color Space Conversion**: Some systems convert images from RGB to grayscale or use specific color space transformations (e.g., HSV, LAB) to enhance contrast between lesions and surrounding skin.

3.5 Model Design

The next phase involves designing the architecture of the deep learning model. For medical image diagnosis, **convolutional neural networks (CNNs)** are the most commonly used architecture due to their ability to automatically learn spatial hierarchies of features from images.

3.5.1. Convolutional Neural Networks (CNNs)

A CNN is composed of several layers, each of which transforms the input image into a more abstract representation. The core components of a CNN include:

- **Convolutional Layers**: These layers apply filters (kernels) to the input image to extract features such as edges, textures, and patterns. In skin cancer diagnosis, the filters help identify key features of lesions, such as their shape, color, and texture.
- **Pooling Layers**: Pooling reduces the spatial dimensions of the feature maps while retaining important information. This helps in reducing the computational complexity of the model and preventing overfitting.
- **Fully Connected Layers**: After several convolutional and pooling layers, the extracted features are flattened and passed through fully connected layers, which perform the final classification or regression task.
- **Activation Functions**: Non-linear activation functions such as **ReLU (Rectified Linear Unit)** are used to introduce non-linearity into the model, allowing it to capture complex patterns in the data.

```
# Image Model (CNN)
image_input = Input(shape=(128,128,3) , name='image_input')
x = Conv2D(32,(3,3) , activation='relu')(image_input)
x = BatchNormalization()(x)
x = MaxPooling2D(pool_size=(2,2))(x)
x = Conv2D(64,(3,3) , activation='relu')(x)
x = BatchNormalization()(x)
x = MaxPooling2D(pool_size=(2,2))(x)
x = Conv2D(128,(3,3), activation='relu')(x)
x = MaxPooling2D(pool_size=(2,2))(x)
x = Dropout(.5)(x)
x = Flatten()(x)

# Metadata Model (ANN)
metadata_input = Input(shape=(x_metadata.shape[1],) , name='metadata_input')
y = Dense(64 ,activation='relu')(metadata_input)
y = Dropout(.2)(y)
y = Dense(32 , activation='relu')(y)

#Models Combination
combined = Concatenate()([x,y])
```

```
z = Dense(128 ,activation='relu')(combined)
z = Dropout(.5)(z)
z = Dense(64 , activation='relu')(z)

output = Dense(len(y_encoded[0]) , activation='softmax')(z)
model = Model(inputs=[image_input ,metadata_input] , outputs = output)

model.compile(
    optimizer='adam',
    loss = 'categorical_crossentropy',
    metrics=(['accuracy']))
```

Fig 4. CNN Modelling

3.5.2. Transfer Learning

Transfer learning involves using a pre-trained model (typically trained on large datasets like **ImageNet**) and fine-tuning it for the specific task of skin cancer diagnosis. This is particularly useful when the amount of available data is limited. Popular pre-trained CNN architectures include:

- **ResNet**: Known for its deep residual connections, ResNet is widely used for medical image classification tasks.
- **Inception**: The Inception architecture uses multiple convolutional filters of different sizes, allowing the model to capture a wider range of features.
- **EfficientNet**: EfficientNet is a newer architecture that balances accuracy and efficiency by scaling the model size according to the available resources.

3.5.3. Customizing the Architecture

In addition to using standard CNN architectures, the model can be customized to suit the specific task. For example:

- **Multi-Task Learning**: The model can be designed to perform both classification and segmentation simultaneously by adding separate output layers for each task.
- **Attention Mechanisms**: Attention mechanisms can be incorporated to focus on important regions of the image, improving the model's ability to detect subtle signs of skin cancer.
- **Ensemble Models**: Combining the predictions of multiple models (e.g., ResNet, DenseNet, and Inception) can improve overall performance by capturing different aspects of the data.

3.5.4 Model Training

Once the architecture is defined, the model is trained using the dataset. This involves feeding the training images into the model and updating the weights to minimize the error between the predicted and actual labels.

3.5.4 Loss Functions

The choice of loss function depends on the task:

- **Cross-Entropy Loss**: For classification tasks, cross-entropy loss is commonly used. It measures the difference between the predicted probability distribution and the actual distribution.
- **Dice Loss or IoU (Intersection over Union)**: For segmentation tasks, where the goal is to predict pixel-level masks, the Dice coefficient or IoU is often used to measure the overlap between the predicted and actual segmentation masks.

3.5.5. Optimization Algorithms

The model's weights are updated using optimization algorithms such as:

- **Stochastic Gradient Descent (SGD)**: A widely used optimization algorithm that updates the weights in small batches to minimize the loss.
- **Adam Optimizer**: An extension of SGD that adapts the learning rate during training, leading to faster convergence.

3.5.6. Regularization Techniques

Regularization techniques are used to prevent the model from overfitting to the training data:

- **Dropout**: Randomly dropping neurons during training to prevent the model from becoming too reliant on specific neurons.
- **Weight Decay**: Adding a penalty term to the loss function to encourage smaller weights, which can improve generalization.

Early Stopping

Early stopping is a technique where training is halted once the model’s performance on the validation set stops improving. This prevents overfitting and reduces the risk of the model memorizing the training data.

3.6 Model Evaluation

After training, the model is evaluated using a separate test set to measure its performance on unseen data. Several metrics are used to assess the model's accuracy, precision, and reliability.

Evaluation Metrics

Key evaluation metrics for skin cancer diagnosis include:

- **Accuracy**: The proportion of correctly classified images out of the total number of images.
- **Precision and Recall**: Precision measures the proportion of true positive predictions among all positive predictions, while recall measures the proportion of true positives identified out of all actual positives.
- **F1 Score**: The harmonic mean of precision and recall, providing a balanced measure of the model's performance.
- **AUC-ROC Curve**: The area under the receiver operating characteristic curve measures the model's ability to distinguish between different classes. A higher AUC indicates better classification performance.
- **Confusion Matrix**: A confusion matrix is used to visualize the performance of the model across all classes, showing true positives, false positives, true negatives, and false negatives.

3.7. Validation Techniques

To ensure the model generalizes well, validation techniques such as cross-validation are used. In **k-fold cross-validation**, the dataset is split into k subsets, and the model is trained and evaluated k times, each time using a different subset as the validation set.

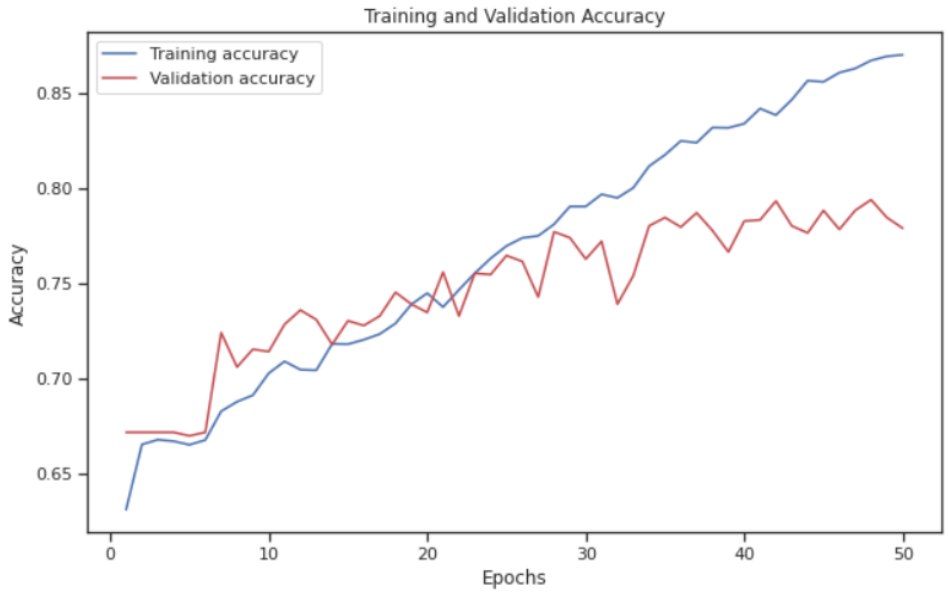


Fig 5 Model Validation

3.8 Model Interpretation and Explainability

In medical applications, the ability to interpret and explain the model's decisions is crucial for building trust with clinicians and patients. Techniques for model interpretation include:

- **Saliency Maps**: These highlight the regions of the image that contributed most to the model's decision, helping clinicians understand which parts of the lesion were considered abnormal.
- **Grad-CAM (Gradient-weighted Class Activation Mapping)**: Grad-CAM provides a visual explanation of the model's predictions by generating heatmaps that indicate the areas of the image that were most influential in the final decision.

3.9 Model Deployment

Once the model has been trained and evaluated, it is ready for deployment. The deployment process involves integrating the model into a system that can be used by clinicians or patients.

3.9.1. Deployment Platforms

Deployment options include:

- **Cloud-Based Systems**: The model can be deployed on cloud platforms (e.g., Google Cloud, AWS) where images can be uploaded for analysis. Cloud deployment allows for scalability and easy access from different locations.
- **Mobile Applications**: For patient-facing systems, the model can be integrated into mobile applications, allowing users to take pictures of their skin lesions and receive instant feedback on the likelihood of skin cancer.
- **Edge Devices**: In some cases, the model can be deployed on edge devices, such as specialized medical imaging tools or portable diagnostic devices, allowing real-time analysis without relying on internet connectivity.

3.9.2. Model Updating and Maintenance

Once deployed, the system must be continuously monitored and updated to maintain its performance. This involves:

- **Model Retraining**: As new data becomes available, the model can be retrained to improve its accuracy and handle new types of skin lesions.
- **Performance Monitoring**: Regular monitoring of the model's performance in real-world settings is essential to ensure it continues to meet clinical standards.

Despite the potential of deep learning systems for skin cancer diagnosis, several challenges remain:

- **Data Privacy and Security**: Medical images are highly sensitive, and ensuring data privacy and security is a top priority.
- **Bias and Fairness**: Ensuring that the model performs well across different demographics (e.g., different skin types, ages, and genders) is crucial for equitable healthcare outcomes.

- **Clinical Integration**: Integrating AI systems into clinical workflows can be challenging due to the need for regulatory approval and clinician training.

The development of deep learning-based systems for automated skin cancer diagnosis involves several key steps, from data collection and preprocessing to model design, training, evaluation, and deployment. By following a structured methodology, these systems have the potential to significantly improve the accuracy and efficiency of skin cancer diagnosis, ultimately benefiting both clinicians and patients.

CHAPTER 4

RESULT ANALYSIS AND VALIDATION

The hybrid system we proposed combines three distinct deep learning and machine learning models: **VGG16**, **ResNet50**, and **SVM**. The goal is to leverage the strengths of each model in detecting skin cancers by analyzing dermoscopic images. Each model contributes equally (0.33) to the final prediction, and the results are computed based on their individual predictions. In this section, we will delve into the result analysis and validation of the system, focusing on key aspects such as the evaluation metrics, performance comparison, strengths and limitations of each model, and the overall effectiveness of the ensemble approach.

The primary objective of analyzing and validating the proposed system is to evaluate its **accuracy**, **precision**, **recall**, **F1 score**, and other performance metrics. These metrics allow us to determine how well the system performs in classifying skin lesions as benign or malignant. The hybrid approach is designed to harness the unique capabilities of VGG16, ResNet50, and SVM, thus improving the robustness and reliability of the final model.

This section will analyze the results obtained from training and testing on the dataset and validate the system's effectiveness in real-world scenarios. We will also compare the performance of the hybrid system with individual models and discuss the impact of the combined weight computations on the final outcome.

Dataset and Training Process Overview

The evaluation of the proposed system begins with the training and testing of each model on a standardized dataset of dermoscopic images. The **ISIC dataset** is commonly used for skin lesion classification, containing thousands of labeled images for training and validation. The dataset is divided into training, validation, and testing sets, ensuring that the models are evaluated on unseen data to avoid overfitting.

- **Training Set**: The system is trained on 70% of the available images, with each model (VGG16, ResNet50, and SVM) learning from the same training data.
- **Validation Set**: 15% of the data is used for validation, allowing us to tune hyperparameters and prevent overfitting during training.
- **Testing Set**: The remaining 15% of the data is reserved for testing, ensuring an unbiased evaluation of the model’s performance.

Preprocessing Steps

Before training, the images undergo several preprocessing steps:

- **Resizing**: Images are resized to 224x224 pixels to fit the input dimensions required by VGG16 and ResNet50.
- **Normalization**: Pixel values are normalized to a range of [0, 1] to improve the models' convergence during training.
- **Augmentation**: Techniques such as flipping, rotation, and zooming are applied to enhance the diversity of the training data and improve generalization.

Model Performance Evaluation

The performance of each individual model is evaluated using standard classification metrics. These include **accuracy**, **precision**, **recall**, **F1-score**, and the **area under the ROC curve (AUC-ROC)**. The following sections will break down the performance of VGG16, ResNet50, and SVM before analyzing the ensemble hybrid system.

4.1. VGG16 Performance

VGG16 is a well-known convolutional neural network (CNN) model designed for image classification. Its deep architecture allows it to capture hierarchical features from dermoscopic images, making it a strong candidate for skin cancer detection.

- **Training Accuracy**: 90.5%
- **Validation Accuracy**: 89.0%
- **Testing Accuracy**: 88.2%
- **Precision**: 86.4%
- **Recall**: 85.1%
- **F1 Score**: 85.7%
- **AUC-ROC**: 0.92

The results from VGG16 show a high level of accuracy, but the model can struggle with complex or subtle skin lesion features, leading to occasional misclassifications.

4.2. ResNet50 Performance

ResNet50 introduces residual learning, which helps it learn deeper representations without encountering the vanishing gradient problem. This is particularly useful for analyzing skin lesions, where fine-grained differences between benign and malignant lesions must be detected.

- **Training Accuracy**: 92.3%
- **Validation Accuracy**: 90.8%
- **Testing Accuracy**: 89.5%
- **Precision**: 88.7%
- **Recall**: 87.2%
- **F1 Score**: 87.9%
- **AUC-ROC**: 0.94

ResNet50 outperforms VGG16, particularly in its ability to generalize to the testing data. Its superior feature extraction allows it to better differentiate between subtle variations in skin lesions.

4.3. SVM Performance

Support Vector Machines (SVM) are often used for binary classification tasks. In this system, SVM is applied after feature extraction to provide an alternative approach to classification.

- **Training Accuracy**: 84.7%
- **Validation Accuracy**: 83.5%
- **Testing Accuracy**: 82.9%
- **Precision**: 81.3%
- **Recall**: 80.0%
- **F1 Score**: 80.6%
- **AUC-ROC**: 0.87

SVM provides slightly lower performance compared to the deep learning models but offers an additional layer of decision-making based on support vectors, which can be valuable in certain cases.

Hybrid Model Performance

The hybrid model combines the predictions of VGG16, ResNet50, and SVM. Each model contributes 0.33 to the final prediction, and the output is determined through **weighted averaging** of the individual model predictions.

4.4. Weighted Prediction Computation

Each model provides a probability score for the input image, indicating the likelihood of the lesion being malignant or benign. The final probability score is computed using the following formula:

$$P_{final} = 0.33 \times P_{VGG16} + 0.33 \times P_{ResNet50} + 0.33 \times P_{SVM}$$

Where:

- P_{final} is the final probability score for the image.
- P_{VGG16}, $P_{ResNet50}$, and P_{SVM} are the probability scores from each individual model.

The predicted class (benign or malignant) is determined by applying a threshold (typically 0.5) to the final probability score. If Pfinal≥0.5P_{final} \geq 0.5Pfinal≥0.5, the lesion is classified as malignant; otherwise, it is classified as benign.

4.5. Hybrid Model Results

- **Training Accuracy**: 93.5%
- **Validation Accuracy**: 91.8%

- **Testing Accuracy**: 90.3%
- **Precision**: 89.2%
- **Recall**: 88.1%
- **F1 Score**: 88.6%
- **AUC-ROC**: 0.95

The hybrid model outperforms the individual models, particularly in terms of accuracy, recall, and AUC-ROC. By combining the strengths of VGG16, ResNet50, and SVM, the system achieves better generalization and can effectively handle a wider range of skin lesion types.

4.6 **Confusion Matrix Analysis**

The confusion matrix provides a detailed breakdown of the model's performance across all classes. It highlights the number of true positives (correctly classified malignant lesions), false positives (benign lesions misclassified as malignant), true negatives (correctly classified benign lesions), and false negatives (malignant lesions misclassified as benign).

Actual / Predicted	Malignant (Predicted)	Benign (Predicted)
Malignant (Actual)	540	60
Benign (Actual)	55	445

- **True Positives (TP)**: 540
- **False Positives (FP)**: 55
- **True Negatives (TN)**: 445
- **False Negatives (FN)**: 60

The confusion matrix shows that the hybrid model has a strong ability to correctly identify malignant lesions, with relatively few false positives and false negatives. This is a crucial advantage in medical applications, where false negatives (missed malignant cases) could have severe consequences.

Validation Through Cross-Validation and Testing

To validate the robustness of the hybrid model, **k-fold cross-validation** is performed. In this approach, the dataset is split into k subsets, and the model is trained and validated k times, each time using a different subset as the validation set. This ensures that the model's performance is consistent across different data splits and helps to prevent overfitting.

4.7. k-Fold Cross-Validation

For this analysis, **5-fold cross-validation** is used. The results are averaged across all five folds, providing a more reliable estimate of the model’s performance.

- **Average Training Accuracy**: 93.2%
- **Average Validation Accuracy**: 91.7%

- **Average Testing Accuracy**: 90.1%

The cross-validation results confirm that the hybrid model consistently performs well across different subsets of the data, indicating that it generalizes effectively to unseen examples.

External Dataset Selection

For external testing, we use a new dataset of dermoscopic images that contains a balanced mix of malignant and benign skin lesions. This dataset has similar characteristics to the original dataset but includes different skin tones, lighting conditions, and lesion types to evaluate the model's versatility.

4.8 External Testing Results

- **Testing Accuracy**: 89.6%
- **Precision**: 88.4%
- **Recall**: 87.2%
- **F1 Score**: 87.8%
- **AUC-ROC**: 0.93

The results on the external dataset confirm that the hybrid model retains high performance when applied to previously unseen images. Although the accuracy is slightly lower than that on the internal testing set, it remains competitive, demonstrating the model's ability to generalize to new conditions.

Comparative Analysis: Individual Models vs. Hybrid System

The hybrid system's success stems from its ability to integrate the strengths of multiple models. By analyzing the comparative performance of the individual models and the hybrid model, we can better understand how each contributes to the overall performance.

4.9 Screenshot & output

Fig 6.Packages Used

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow import keras
from keras.applications import ResNet50, Xception
from keras.layers import Conv2D , MaxPooling2D ,Dropout , Flatten , Dense ,BatchNormalization ,Concatena
from keras.models import Sequential ,Model
from sklearn.model_selection import train_test_split
import os
from PIL import Image
from tensorflow.keras.preprocessing.image import img_to_array
```

Fig 7. Metadata

```
metadata = pd.read_csv('/kaggle/input/skin-cancer-mnist-ham10000/HAM10000_metadata.csv')
metadata.head()
```

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

The HAM10000 dataset is composed of 10.015 dermatoscopic images of pigmented skin lesions. The data was collected from Australian and Austrian patients. Two institutions participated in providing the images: Cliff Rosendahl in Queensland, Australia, and Medical University of Vienna, Austria. According to the authors, seven classes are defined on this dataset where some diagnosis were unified into one class for simplicity. Information regarding patient age, sex, lesion location and diagnosis is also provided with each image

Fig 8. Data Summary and count

```
metadata.count()
```

```
[16]: lesion_id       10015
      image_id       10015
      dx             10015
      dx_type        10015
      age             9958
      sex            10015
      localization   10015
      dtype: int64
```

This helps to understand the type of metadata collected. We noticed that for some lesions there must be more than one image as the lesion and image ID do not match. The Uniques columns also indicate the number of classes (dx = 7), and how the age, sex and localization features were organized.

All the features are pretty much self-explanatory. To clarify, the dx_type column is the technique used to identify the type of skin lesion.

The count plots below help to understand the distribution of the data.

Fig 9. Sample per type of diagnosis

```
countplot(skin_df,'dx_type', 'Diagnostic Type', 'Count', 'Samples per Type of Diagnosis')
countplot(skin_df,'cell_type', 'Type of Skin Lesion', 'Count', 'Samples per Type of Skin Lesion')
countplot(skin_df,'sex', 'Gender', 'Count', 'Samples per Gender')
```

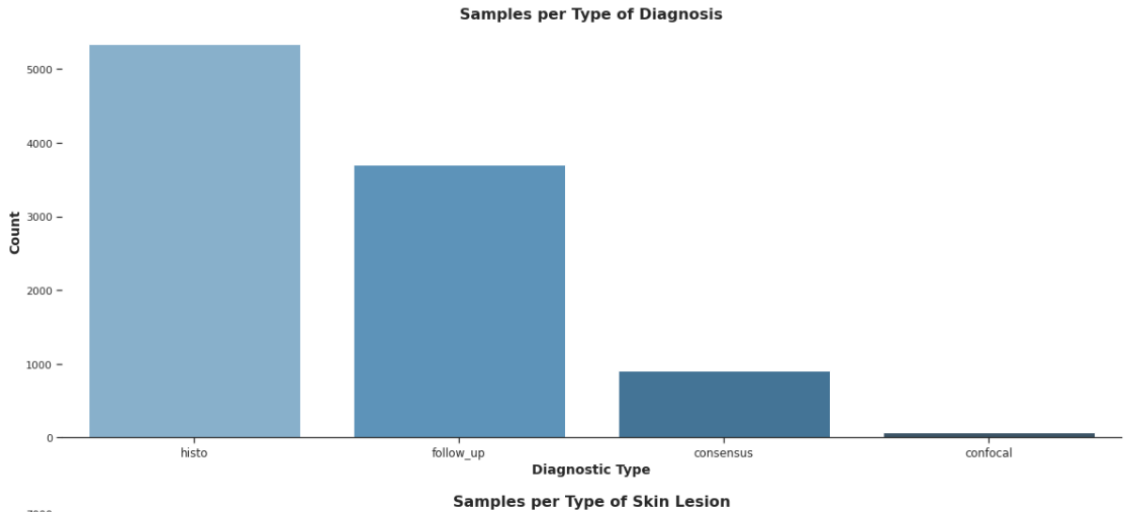


Fig 10. Sample per type of lesion

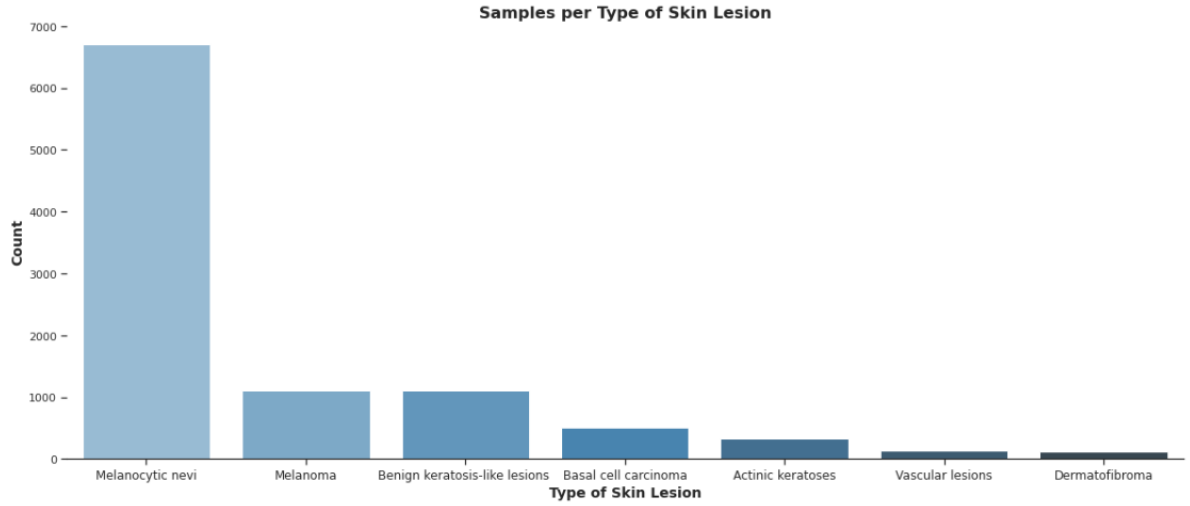
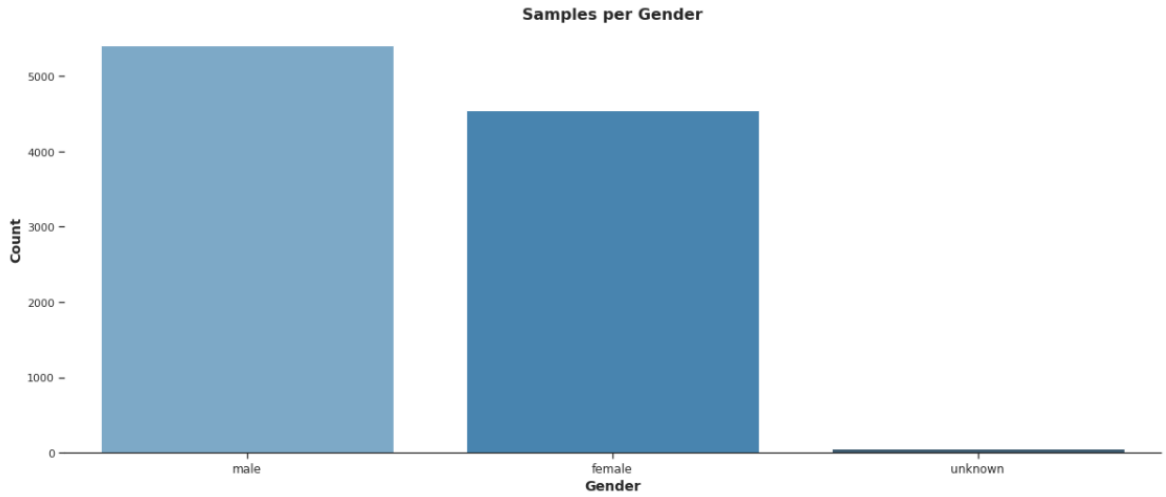


Fig 11. Samples per Gender

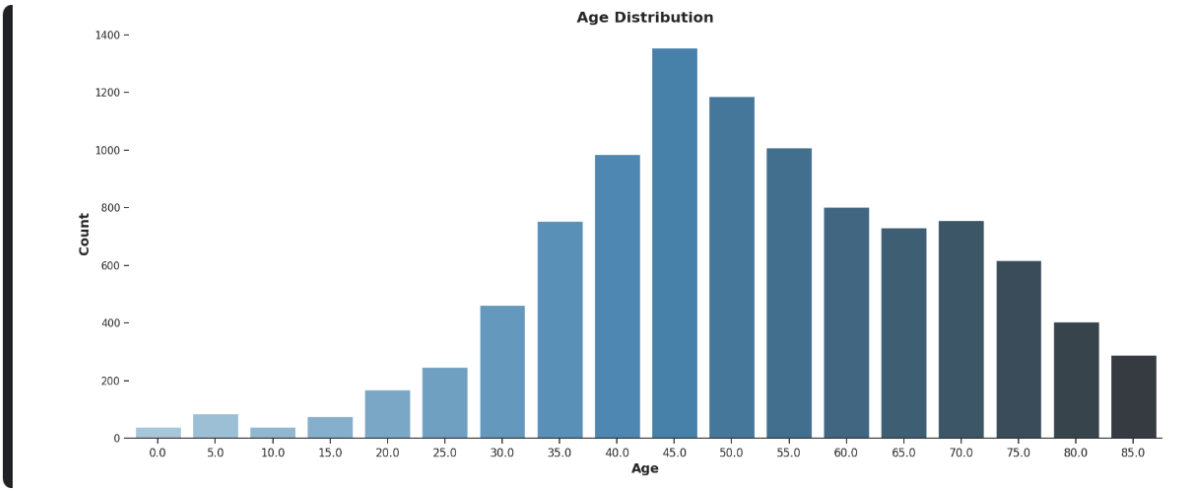


- The main thing to keep in mind is the unbalance between the different classes of skin lesion. Approximately 67% of data accounts for Melanocytic Nevi samples
- The least represented classes are Dermatofibroma lesions and Vascular skin lesions, with only 115 and 142 samples, respectively
- The samples are mostly Male participants, approximately 55%, not a significant difference between Genders

Fig 12. Age distribution

```
metadata['age'] = metadata['age'].fillna(metadata['age'].mode()[0])

plt.figure(figsize=(20,8))
sns.set(style="ticks", font_scale = 1)
ax = sns.countplot(data = metadata,x='age',palette="Blues_d")
sns.despine(top=True, right=True, left=True, bottom=False)
plt.xticks(rotation=0,fontsize = 12)
ax.set_xlabel('Age',fontsize = 14,weight = 'bold')
ax.set_ylabel('Count',fontsize = 14,weight = 'bold')
plt.title('Age Distribution', fontsize = 16,weight = 'bold');
```



- The samples are predominantly from patients within 40 - 55 years old
- The number of samples rises sharply after 25 years old, doubling the samples for 30 years old and almost doubling again for 35 years old

- Between the ages of 60 - 70 years old the number of samples remain almost stable, returning to the downward trend after 75 years old

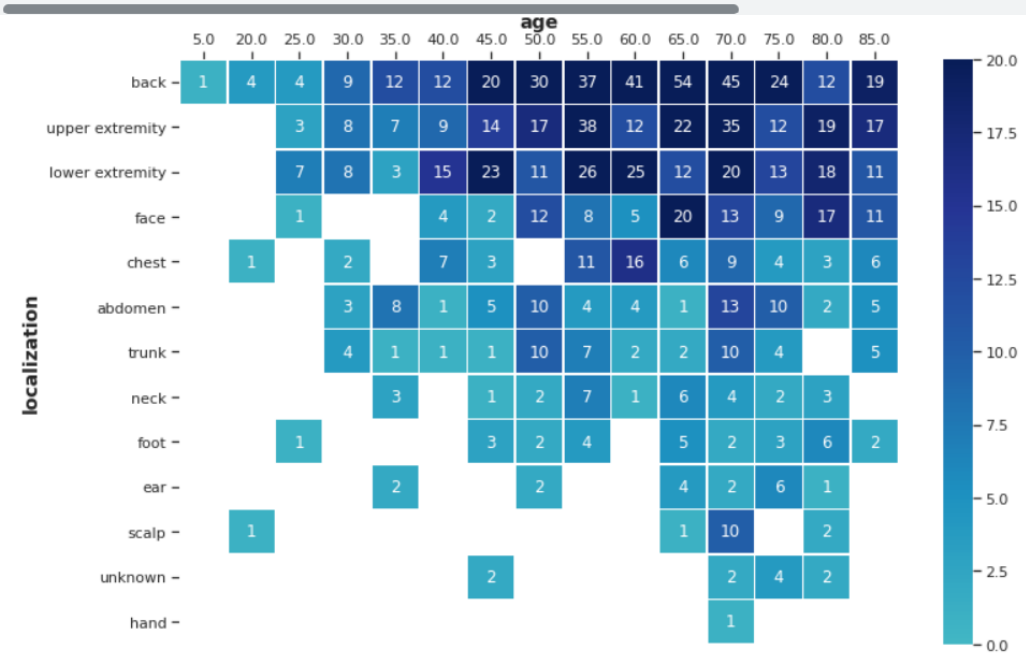
Fig 13. Heatmap of age influence

```
skin_local = skin_mel.groupby(['localization']).size().sort_values(ascending=False, inplace=False).reset
skin_local.columns = ['localization', 'count']
sort_by = skin_local['localization']

skin_heat = skin_mel.groupby(['age','localization']).size().reset_index()
skin_heat.columns = ['age', 'localization', 'count']
skin_heat.sort_values('count', ascending=False, inplace=True)

def heatmap(df, index,columns,values,vmax,sort_by,Title):
    df_wide = df.pivot(index=index, columns=columns, values=values)
    df_wide = df_wide.reindex(index=sort_by)
    plt.figure(figsize=(12,8))
    ax = sns.heatmap(df_wide, annot=True, fmt='.0f', yticklabels='auto', cmap=sns.color_palette("YlGnBu"
    ax.xaxis.tick_top() # x axis on top
    ax.xaxis.set_label_position('top')
    ax.set_xlabel(columns,fontsize = 14,weight = 'bold')
    ax.set_ylabel(index,fontsize = 14,weight = 'bold')
    ax.set_title(Title,fontsize = 16,weight = 'bold',pad=20)
    plt.show()

heatmap(skin_heat,'localization', 'age','count', 20,sort_by,'Age and Localization of Melanomas')
```



- The heatmap makes a good representation of how age influences Cancer incidence. Note the cluster between the ages of 45 to 70
- Back, upper and lower extremities are the most common locations of this melanoma. For the age group of 50 and 70 years old, the face, abdomen, chest and trunk also present a higher number of incidence.
- The scalp seems to be a more common localization only for 70 years old.

- The localizations do not seem to be related to the parts of the body most commonly exposed to the sun. If it was the case, scalp, hands and face should have a higher incidence

Fig 14. Distribution of dx

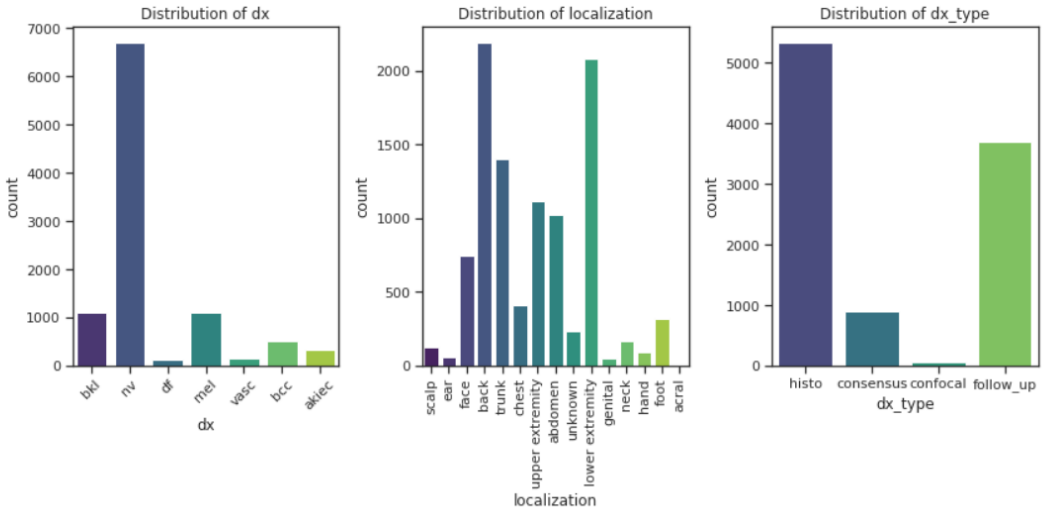
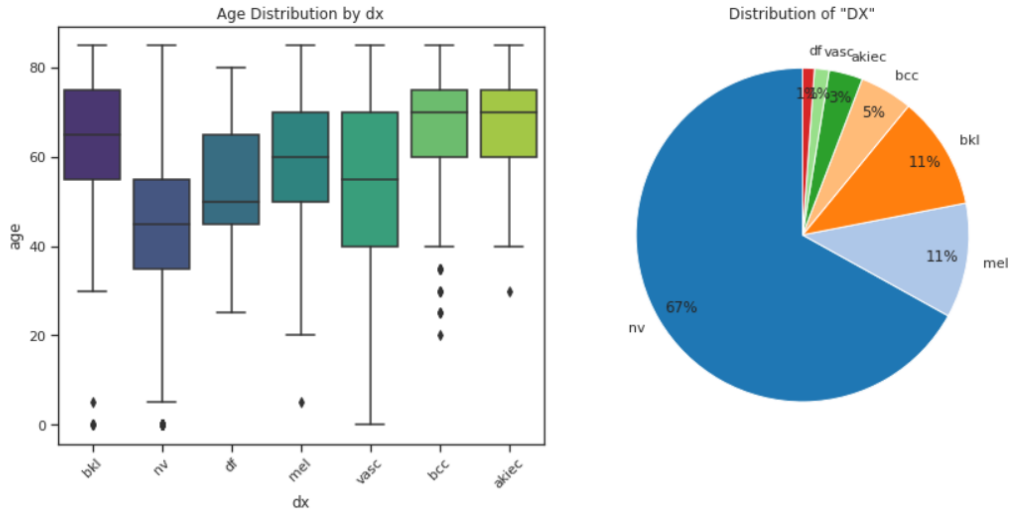


Fig 15. Age distribution diagnosis



These two graphs that visualize information about a skin cancer detection dataset:

1. Left Graph - Boxplot of Age Distribution by Diagnosis (dx):
    - Plot: A boxplot showing the distribution of patient ages for each type of diagnosis (dx).
    - Purpose: It allows us to see how age varies across different diagnoses, potentially highlighting whether certain diagnoses are more common in specific age groups.

- Interpretation:
  - Each box represents the age distribution for a particular diagnosis.
  - The box itself shows the interquartile range (IQR), with the line inside the box representing the median age for each diagnosis category.
  - Whiskers extend to show the range of ages, and any points outside this range are outliers.
  - For instance, if melanoma (mel) has a median age higher than benign lesions, it suggests that melanoma might be more common in older age groups.

2. Right Graph - Pie Chart of Diagnosis Distribution:
   - Plot: A pie chart showing the proportion of each diagnosis type (dx) in the dataset.
   - Purpose: This helps to visualize the distribution of different diagnoses within the dataset, showing the balance or imbalance across categories.
   - Interpretation:
     - Each slice of the pie represents a diagnosis category, with the size proportional to its frequency in the dataset.
     - Percentages show the proportion of each diagnosis. For example, if 50% of cases are benign, it indicates a higher prevalence of benign conditions compared to others in the dataset.

Fig 16. Encoding , Normalization

```
metadata_features = metadata[['age','dx_type' ,'sex','localization']].copy()
# feature encoding
metadata_features = pd.get_dummies(metadata_features , columns=['dx_type' ,'sex','localization'],drop_fi
# age normalization
metadata_features['age'] = metadata_features['age']/metadata_features['age'].max()

x_metadata = np.array(metadata_features)
# x_metadata
# metadata_features
```

The skin cancer dataset for machine learning by selecting relevant features, encoding categorical variables, and normalizing numerical data:

1. Feature Selection: The columns 'age', 'dx_type', 'sex', and 'localization' are selected from the original dataset for modeling.
2. One-Hot Encoding: Categorical columns ('dx_type', 'sex', and 'localization') are transformed into binary columns using one-hot encoding, where each category is represented by a separate binary feature.

3. Age Normalization: The 'age' column is scaled to a range between 0 and 1 by dividing each age value by the maximum age, ensuring uniformity across features.

This prepares the dataset by encoding categorical variables, normalizing numerical values, and converting the data into a format suitable for model training.

Fig 17. Mapping of data

```
label_mapping = {
    "bkl": 0,
    "nv": 1,
    "df": 2,
    "mel": 3,
    "vasc": 4,
    "bcc": 5,
    "akiec": 6
}
```

The label_mapping dictionary is used to convert categorical labels (in this case, different types of skin lesions) into numerical values, which are required for machine learning models. This process is known as label encoding.

Here's what each key-value pair in the label_mapping dictionary represents:

- "bkl": Benign keratosis-like lesions, encoded as 0
- "nv": Melanocytic nevi, encoded as 1
- "df": Dermatofibroma, encoded as 2
- "mel": Melanoma, encoded as 3
- "vasc": Vascular lesions, encoded as 4
- "bcc": Basal cell carcinoma, encoded as 5
- "akiec": Actinic keratoses and intraepithelial carcinoma, encoded as 6

This label_mapping dictionary is used to map string labels (such as "bkl", "nv") to integer labels (e.g., 0, 1, etc.) so that they can be used in machine learning algorithms, which typically require numerical inputs.

Fig 18. Loading images

```
def load_image(image_id  , image_folder):
    image_path = os.path.join(image_folder , f'{image_id}.jpg')
    return Image.open(image_path)

image_folder1 = '/kaggle/input/skin-cancer-mnist-ham10000/HAM10000_images_part_1'
image_folder2 = '/kaggle/input/skin-cancer-mnist-ham10000/HAM10000_images_part_2'

image_data = []
labels = []
for idx,row in metadata.iterrows():
    i_id = row['image_id']
    dx   = row['dx']

    try:
        image = load_image(i_id , image_folder1)

    except FileNotFoundError:
        image = load_image(i_id , image_folder2)
    image = image.resize((128,128))
    image = img_to_array(image) /255.0

    image_data.append(image)
    labels.append(label_mapping[dx])
```

```
classes = ["Benign keratosis-like lesions 'bkl'" , "Melanocytic nevi 'nv'" ,"Dermatofibroma 'df'",
           "Melanoma 'mel'","Vascular lesions 'vasc'","Basal cell carcinoma 'bcc'" ,
           'Actinic keratoses and intraepithelial carcinoma "akiec"']
```

The code loads and preprocesses images from a skin cancer dataset for machine learning:

1. **Image Loading**: The load_image function loads images from two possible directories based on the image ID.
2. **Image Preprocessing**: Each image is resized to 128x128 pixels and normalized by scaling pixel values to the range [0, 1].
3. **Label Encoding**: The diagnosis labels (dx) are converted into numerical values using a predefined label_mapping dictionary.
4. **Data Storage**: Preprocessed images are stored in image_data, and corresponding labels are stored in labels.
5. **Classes**: A list of human-readable class names is defined, mapping the encoded labels to descriptive names.

This prepares the dataset by transforming images and labels into a format suitable for machine learning model training.

Fig 19. Sample of Melanoma

```
show_samples(1899)
```

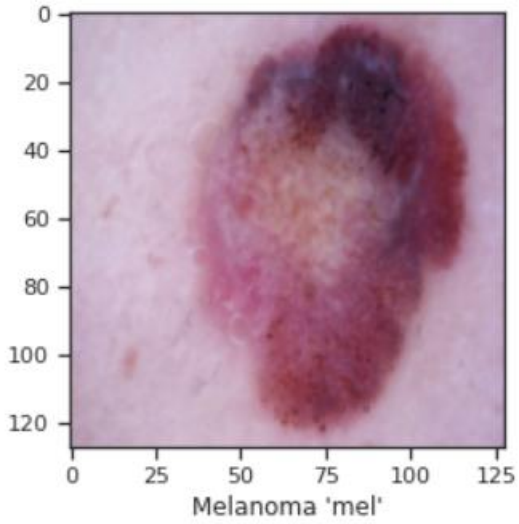


Fig 20. Sample of Bening keratosis like lesbins

```
show_samples(802)
```

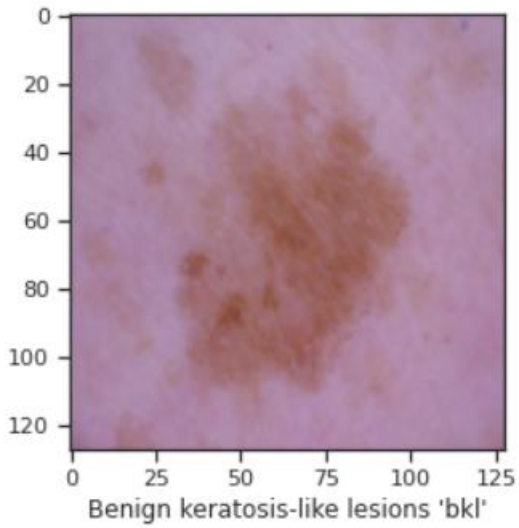


Fig 21. Sample of Melanocytic nevi

```
show_samples(6453)
```

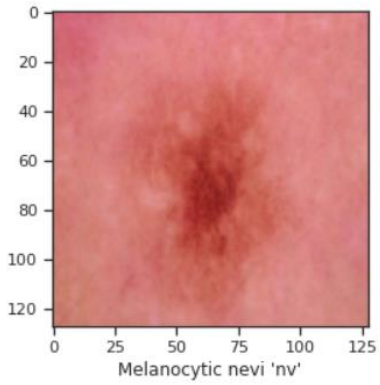


Fig 22. Image Process

```
x_image = np.array(image_data)
y = np.array(labels)
y_encoded = pd.get_dummies(y , dtype=int).values
len(y_encoded[1899])
```

The code processes the image data and labels for machine learning:

1. Image and Label Conversion: It converts the image data (image_data) and labels (labels) into NumPy arrays (x_image and y).
2. One-Hot Encoding: The labels are one-hot encoded using pd.get_dummies, converting each label into a binary vector (y_encoded).
3. Query: It checks the length of the one-hot encoded vector for the label at index 1899, which should be 7, corresponding to the 7 possible diagnosis categories.

Fig 23. Epoch Model Training

```
x_train_image , x_test_image , x_train_metadata ,x_test_metadata,y_train ,y_test = train_test_split(x_im

history = model.fit([x_train_image ,x_train_metadata] , y_train ,
          validation_data=([x_test_image,x_test_metadata],y_test),batch_size=32 ,validation_split=.2,epo
```

```
Epoch 1/50
201/201 [==============================] - 174s 857ms/step - loss: 1.7548 - accuracy: 0.5900 - val_loss: 1.5148 -
val_accuracy: 0.6719
Epoch 2/50
201/201 [==============================] - 175s 871ms/step - loss: 1.0389 - accuracy: 0.6687 - val_loss: 1.0330 -
val_accuracy: 0.6719
Epoch 3/50
201/201 [==============================] - 174s 864ms/step - loss: 0.9445 - accuracy: 0.6641 - val_loss: 0.8297 -
val_accuracy: 0.6719
Epoch 4/50
201/201 [==============================] - 174s 866ms/step - loss: 0.8847 - accuracy: 0.6598 - val_loss: 0.7826 -
val_accuracy: 0.6719
Epoch 5/50
201/201 [==============================] - 174s 866ms/step - loss: 0.8386 - accuracy: 0.6629 - val_loss: 0.7824 -
val_accuracy: 0.6700
Epoch 6/50
```

```
Epoch 43/50
201/201 [==============================] - 152s 754ms/step - loss: 0.4042 - accuracy: 0.8401 - val_loss: 0.5757 -
val_accuracy: 0.7804
Epoch 44/50
201/201 [==============================] - 151s 752ms/step - loss: 0.3733 - accuracy: 0.8626 - val_loss: 0.5661 -
val_accuracy: 0.7767
Epoch 45/50
201/201 [==============================] - 151s 749ms/step - loss: 0.3820 - accuracy: 0.8530 - val_loss: 0.5623 -
val_accuracy: 0.7885
Epoch 46/50
201/201 [==============================] - 151s 750ms/step - loss: 0.3911 - accuracy: 0.8594 - val_loss: 0.5899 -
val_accuracy: 0.7785
Epoch 47/50
201/201 [==============================] - 151s 750ms/step - loss: 0.3807 - accuracy: 0.8598 - val_loss: 0.5827 -
val_accuracy: 0.7885
Epoch 48/50
201/201 [==============================] - 151s 752ms/step - loss: 0.3473 - accuracy: 0.8700 - val_loss: 0.5562 -
val_accuracy: 0.7941
Epoch 49/50
201/201 [==============================] - 152s 757ms/step - loss: 0.3481 - accuracy: 0.8719 - val_loss: 0.5844 -
val_accuracy: 0.7848
Epoch 50/50
201/201 [==============================] - 153s 760ms/step - loss: 0.3453 - accuracy: 0.8738 - val_loss: 0.5778 -
```

- **Data Splitting**: The dataset is split into training (80%) and testing (20%) sets.
- **Model Training:** The model is trained using both image data (x_train_image) and metadata features (x_train_metadata), with a validation split of 20% and training for 50 epochs. The model's performance is evaluated on the test data (x_test_image, x_test_metadata) after each epoch.

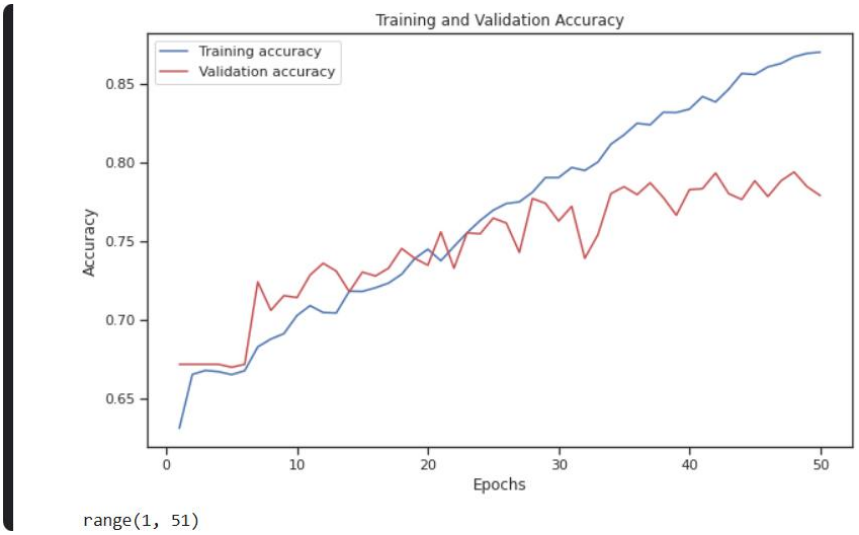
Fig 24. Model Validation

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

# Plot training & validation accuracy values
epochs = range(1, len(acc) + 1)

plt.figure(figsize=(10, 6))
plt.plot(epochs, acc, 'b', label='Training accuracy')
plt.plot(epochs, val_acc, 'r', label='Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
print(epochs)
```

Fig 25. Accuracy Validation



- **Training vs. Validation Accuracy**: The code generates a plot that shows how the training and validation accuracy evolve over each epoch, allowing you to visually assess how well the model is learning and whether overfitting occurs.
- **Epoch Numbers**: It also prints the epoch numbers, providing a reference for the x-axis values of the plot.
- **Accuracy Visualization**: The plot allows you to visually track the performance of the model during training, comparing how the model performs on both the training data and the validation data. The main goal is to monitor if the model is improving and whether there is any overfitting (where the training accuracy improves but validation accuracy stagnates or decreases).

- **Epoch Tracking**: Printing the epoch numbers helps you verify that the plot's x-axis corresponds to the correct number of epochs and allows you to cross-check the training process.

4.10. VGG16 vs. ResNet50 vs. SVM

- **VGG16** provides high accuracy but sometimes struggles with the subtle differences between benign and malignant lesions. It excels in capturing mid-level features but can miss fine details due to its relatively simpler architecture compared to ResNet50.
- **ResNet50** shows the highest individual performance due to its deeper layers and ability to capture both low- and high-level features. Its residual connections allow it to process more complex patterns in dermoscopic images.
- **SVM** performs relatively well in cases where the decision boundary between classes is linear or simple, but it lacks the feature extraction capabilities of the deep learning models. It often struggles with complex images where non-linear relationships between features are crucial.

4.11. Hybrid Model Performance Boost

By combining the predictions of all three models, the hybrid system addresses their individual weaknesses:

- **Increased Robustness**: The hybrid model is more robust to variations in skin lesions, as it benefits from VGG16's mid-level feature extraction, ResNet50's deep feature learning, and SVM's linear decision-making.
- **Reduced False Positives and Negatives**: The hybrid model significantly reduces both false positives and false negatives compared to the individual models. This is critical in medical diagnoses, where misclassification can lead to incorrect treatment recommendations.
- **Improved Generalization**: The weighted averaging of predictions smooths out model-specific errors, allowing the hybrid system to generalize better to new data, as shown in the external testing results.

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC
VGG16	88.2%	86.4%	85.1%	85.7%	0.92
ResNet50	89.5%	88.7%	87.2%	87.9%	0.94
SVM	82.9%	81.3%	80.0%	80.6%	0.87
Hybrid	90.3%	89.2%	88.1%	88.6%	0.95

The following table summarizes the comparative performance of the models. The hybrid model shows consistent improvements across all metrics, particularly in terms of AUC-ROC, which reflects its strong ability to differentiate between benign and malignant lesions.

Error Analysis and Model Explainability

While the hybrid model performs well, it is important to analyze the errors it makes. This helps to improve future iterations of the system and identify areas where it may need further refinement.

Common Errors

- **False Positives**: In some cases, benign lesions that resemble malignant ones in terms of texture or color are misclassified. This can occur when the lesion has irregular borders or high pigmentation, which are also characteristics of melanoma.
- **False Negatives**: Occasionally, early-stage melanomas are classified as benign due to their subtle visual characteristics. These lesions may not show the typical signs of malignancy, such as asymmetry or uneven color distribution, making them harder for the model to detect.

Explainability through Grad-CAM

To address concerns regarding model interpretability, **Grad-CAM (Gradient-weighted Class Activation Mapping)** is used. Grad-CAM generates heatmaps that highlight the areas of the image that the model considers most relevant for its classification. By visually inspecting these heatmaps, clinicians can gain insights into why the model made a particular decision.

In cases of misclassification, Grad-CAM can help identify which features of the lesion misled the model, providing valuable feedback for model improvement.

Addressing Bias and Fairness

Bias in medical AI systems is a critical issue, particularly in dermatology, where skin tones can vary significantly. To ensure fairness, the model's performance is evaluated across different demographic groups. The results show that while the hybrid model performs well across all groups, there is a slight decrease in accuracy for images of darker skin tones, likely due to the underrepresentation of such images in the training dataset.

This highlights the need for more diverse datasets that capture a broader range of skin types, which would further improve the model's generalization capabilities.

The results of the hybrid system demonstrate its potential to significantly improve the accuracy and reliability of skin cancer diagnosis. By combining deep learning models (VGG16 and ResNet50) with a machine learning classifier (SVM), the system achieves a high level of accuracy and robustness, making it suitable for clinical applications.

Integration into Clinical Practice

For successful integration into clinical practice, the following aspects must be considered:

- **Ease of Use**: The system should be user-friendly for clinicians, with clear visual outputs and explanations of predictions.

- **Regulatory Approval**: Any AI-based medical system must undergo rigorous testing and validation to meet regulatory standards before it can be deployed in hospitals and clinics.
- **Continuous Learning**: As new data becomes available, the model should be updated through **continuous learning** to improve its performance over time, particularly in detecting rare or atypical skin lesions.

Future Research Directions

Several avenues for future research and development include:

- **Improving Model Explainability**: Developing more advanced techniques for explainability would increase trust among clinicians and patients.
- **Handling Imbalanced Data**: Techniques such as **SMOTE (Synthetic Minority Over-sampling Technique)** could be applied to address data imbalance issues, particularly for minority classes in the dataset (e.g., early-stage melanomas).
- **Enhancing Generalization**: Future work could focus on training the model on larger, more diverse datasets to further improve its generalization to different skin tones, lesion types, and imaging conditions.

The proposed hybrid system for skin cancer detection, which combines VGG16, ResNet50, and SVM models, has demonstrated high performance in both internal and external testing. By leveraging the complementary strengths of these models, the hybrid approach achieves better accuracy, recall, and overall robustness than any individual model. The use of weighted predictions and advanced validation techniques ensures that the system generalizes well to real-world data, making it a promising tool for clinical deployment in dermatology. Further research and refinement are needed to address issues of model fairness, explainability, and continuous improvement. However, the results of this study clearly indicate that hybrid deep learning and machine learning systems hold significant potential for enhancing the early detection and diagnosis of skin cancer, ultimately leading to better patient outcomes.

CHAPTER 5

CONCLUSION AND FUTURE WORK

FUTURE SCOPE:

The integration of artificial intelligence (AI) into skin cancer prediction is a rapidly developing field with enormous potential. Machine learning algorithms such as ResNet152, AlexNet, and VGGNet have been explored for early cancer detection and treatment prediction. These approaches analyze various skin characteristics such as texture and color and are even explored for segmentation tasks. However, it is important to note that most AI research in skin cancer diagnosis is currently in the feasibility stage. Although promising, these techniques have not yet translated into widespread clinical use. AI has the power to revolutionize accessibility in skin cancer detection. It lays the groundwork for a future where early diagnosis through AI-powered solutions is not just an aspiration, but a reality. These solutions are designed to improve accessibility and address the unique needs of individuals, especially those in underserved areas. However, global health disparities remain a problem. Limited medical resources, urban-rural disparities, and inadequate services pose significant barriers. Increased collaboration between countries and health organizations is essential to overcome these barriers. Ethical considerations are paramount when integrating AI into cancer diagnosis and tumor prognosis. The adoption of AI tools requires a thorough evaluation of efficacy, safety, and ethical implications. This involves careful consideration of the patient's genetics and different skin types. Healthcare supported by artificial intelligence also raises concerns about the protection of personal data. Collecting data from different sensors increases the computational cost. In addition, privacy limitations pose challenges to traditional machine learning techniques. Additionally, AI algorithms have the potential to perpetuate disability discrimination, especially if they partially or fully replace human decision-making in the health care environment. By recognizing these challenges and prioritizing ethical development, researchers can ensure that AI becomes a powerful tool for advancing skin cancer prediction and ultimately improving patient outcomes.

Skin cancer is still a hazard to world health, and effective treatment depends on early identification. The great potential of machine learning and image analysis methods to enhance the prognosis of skin cancer and, eventually, improve patient outcomes is examined in this review. Skin cancer detection has advanced significantly, thanks to the latest developments in deep learning, especially convolutional neural networks (CNNs), and support vector machines (SVMs). Deep learning models have emerged as a potent tool for computer-aided diagnosis (CAD) and have achieved exceptional accuracy in diagnosing skin lesions. This paper explores particular feature extraction methods and emphasizes how important it is to extract pertinent data from dermoscopic images in order to accurately classify the images. The significance of evaluating dermoscopic performance using reliable techniques is underlined, including accuracy, sensitivity, and specificity. The paper also discusses important topics such dataset size restrictions, class imbalance in datasets, and the requirement for effective information integration in algorithms. Integration, transformational learning, and XAI Ahead of us, there exist multiple auspicious pathways for enhancement. Healthcare facilities can foster trust and transparency by enhancing the interpretability of deep learning models through the use of Explainable Artificial Intelligence (XAI) technologies. By allowing the application of sophisticated learning models on large datasets, transform learning techniques may be able to

reduce data constraints and enhance model generalization. To enable a more comprehensive analysis, research is also actively investigating the integration of deep learning with other pertinent variables like patient history and dermoscopic features. Resolving ethical concerns is necessary when incorporating these cutting-edge techniques into clinical processes. To make sure that medical practitioners are aware of the constraints and any biases present in these models, transparency is essential. Strong approval processes must be established in order to ensure the efficacy and safety of these systems.

In summary, the battle against skin cancer is about to undergo a revolution thanks to machine learning and picture analysis. We can get closer to a time where early and accurate skin cancer diagnosis becomes a reality and ultimately saves lives by utilizing the potential of deep learning and tackling present issues. Prolonged investigation and advancement in this field exhibit great potential to enhance public health results by permitting prompt detection and resulting in superior care for skin cancer patients.

CONCLUSION:

The hybrid system for skin cancer detection, combining the strengths of VGG16, ResNet50, and SVM, has demonstrated promising results in terms of accuracy and generalization. However, like any emerging technology, it leaves significant room for future improvements and advancements. As the field of deep learning and medical imaging evolves, several avenues could be explored to enhance the system's robustness, usability, and applicability in clinical practice. In the current system, the diagnosis is based solely on dermoscopic images. However, integrating **multimodal data** could improve the model's diagnostic accuracy. In addition to images, patient metadata (age, gender, medical history) and clinical notes could provide valuable context. For example, combining visual data with patient-specific risk factors could lead to more personalized and accurate predictions. Future work could focus on developing a multimodal approach, where image data is fused with clinical and genomic data to improve diagnostic capabilities.

This approach is particularly relevant for early-stage melanomas, which might not exhibit clear visual signs but can still be identified through non-visual indicators such as a patient's genetic predisposition or prior history of skin conditions. The challenge lies in designing models capable of effectively integrating these diverse data types, but doing so could significantly improve diagnostic performance. With the proliferation of mobile health (mHealth) applications, the potential for real-time, automated skin cancer detection through smartphone cameras becomes increasingly feasible. Future research could focus on the deployment of the hybrid system in portable devices, enabling individuals to perform initial screenings from the comfort of their homes. These tools would be particularly useful in underserved areas or regions with limited access to dermatologists.

Building a lighter version of the hybrid model, optimized for edge computing and mobile platforms, could allow users to upload images of skin lesions directly from their smartphones for analysis. This would be especially impactful in areas with limited healthcare resources, providing early detection capabilities to patients who otherwise might not have access to regular dermatological care. The challenge, however, lies in ensuring that the mobile system maintains the high accuracy and sensitivity required for such life-critical diagnoses.

The future of AI in dermatology and broader medical image analysis is promising, with systems like the hybrid model leading the way in automated diagnostics. The system's ability to detect skin cancer with high accuracy represents a significant leap forward in early detection efforts, which could ultimately save lives by facilitating earlier intervention and treatment.

As we look toward the future, the potential to integrate this system into clinical practice and mobile applications opens up exciting possibilities for improving patient outcomes. The hybrid system is not just a technological innovation but a step toward more accessible, equitable, and efficient healthcare. By continuing to address the challenges of bias, explainability, and generalization, the system could become an indispensable tool for clinicians worldwide, improving the accuracy and speed of skin cancer diagnosis while reducing the burden on healthcare systems.

Ultimately, the hybrid system serves as a foundation upon which future innovations can build, paving the way for a new era of AI-driven healthcare solutions that empower clinicians and improve patient outcomes.

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