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SKIN LESIONS DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Skin Lesions Detection Using Convolutional Neural Network

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SUPERVISOR APPROVAL

SKIN LESIONS DETECTION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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This proposal was prepared under supervision of the project supervisor, Dr Habibah Binti Ismail. It was submitted to the Faculty of Computing, Informatics and Mathematics, and was accepted in partial fulfillment of the requirements for the degree of Bachelor of Computer Science (Hons.)

Approved by

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JANUARY 2024

STUDENT DECLARATION

I certify that this thesis and the project to which it refers is the product of my own work and that any idea or quotation from the work of other people, published or otherwise, are fully acknowledged in accordancewith the standard referring practices of the discipline.

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ABSTRACT

Skin cancer poses a significant health concern worldwide, emphasizing the need for effective early detection methods to enhance treatment outcomes and patient prognosis. Early detection of skin lesions is crucial as it increases the chances of identifying potentially cancerous growths, enabling timely intervention and improving overall treatment outcomes. Delayed detection may lead to advanced stages of disease, making it more challenging to treat successfully. Skin lesions can be classified as benign or malignant. Individuals with suspected skin lesions are strongly encouraged to consult healthcare professionals for a comprehensive evaluation. This study introduces the skin lesions detection system using convolutional neural network. The system was developed to detect the human skin whether it is normal or lesions skin. The system incorporates image preprocessing, including resizing and normalization, to enhance feature extraction. Utilizing the powerful CNN model known for its proficiency in learning hierarchical representations from image data, the system achieves an impressive accuracy of 98%.

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CHAPTER 1

INTRODUCTION

This chapter will briefly discuss the project background such as background of study, problem statement, objective of this project, project scope, project significance, overview of research framework.

1.1 Background of Study

Skin cancer is a major public health concern, with millions of new casesdiagnosed every year. Early detection is crucial for successful treatment, and traditional diagnosis methods rely heavily on visual inspection by dermatologists. However, this approach can be time-consuming and subjective, leading to potential diagnostic errors. Automated skin lesiondetection systems using machine learning algorithms have shown promise in improving the accuracy and efficiency of skin cancer diagnosis, but further research is needed to optimize these systems (Andre Esteva, 2017). Skin lesions refer to any abnormality or change in the appearance of the skin. They can range from benign moles or freckles to cancerous growths, and can be caused by a variety of factorsincluding sun exposure, infections, and genetics.

A skin lesion is a growth or appearance of the skin that is abnormal concerning the surrounding skin. Primary and secondary skin lesions are the two types of skin lesions. Primary skin lesions are abnormal skin conditions that can develop over time or be present at birth. Secondary skin lesions can develop from primary skin lesions that have been exacerbated or altered. When a mole is scraped until it bleeds, the crust that forms, as a result, develops a secondary skin lesion. Dermatologistspropose one of three treatments for afflicted skin, depending on the typeof lesion: home care, medicines, or surgery. Regardless of how innocent they appear such as a few sorts of skin lesions may be pretty risky to the patients, since they will indicate the presence of malignancy and require surgical removal (Shetty et al., 2022)

For the efficient treatment of a variety of skin illnesses, early detection and precise diagnosis of skin lesions are crucial. The majority of skin lesion diagnoses in the past relied on visual examination and clinical judgment. More objective and precise techniques for identifying and categorizing skin lesions have, however, evolved as a result of technological and medical imaging improvements. In recent years, therehas been a growing interest in the use of artificial intelligence and machine learning algorithms for skin lesion detection and classification. These methods use computer vision techniques to analyze images of skin lesions, allowing for more precise and accurate diagnosis. The development of these technologies has led to significant improvementsin the diagnosis and treatment of various skin diseases, including melanoma and other forms of skin cancer. Overall, the study of skin lesions is an important field of research that has the potential to improve patient outcomes, reduce healthcare costs, and advance medical knowledge.

1.2 Problem Statement

Areas of your skin that are different from the surrounding skin calledskin lesions. Skin lesions are frequent and may arise from an injury or other skin damage, such as a sunburn. Infections or autoimmune disorders may be present as a symptom of underlying problems in some cases. The majority of skin lesions are benign (noncancerous) and safe, but they can also signal a more dangerous condition. Skin cancer is one of the most common types of cancer, and early detection is critical for successful treatment. Traditional skin cancer diagnosis relies heavily on visual inspection by dermatologists, which can be subjective and time-consuming. Automated skin lesion detection systems using machine learning algorithms have shown promising results in improving the accuracy and efficiency of skin cancer diagnosis, but there is still room for improvement (Wang et al., 2023)

The explanation of the problem for skin lesion detection is that conventional methods, such as clinical judgment and visual inspection, can be subjective and prone to inaccuracy. Skin lesion misdiagnosis can result in delayed or ineffective treatment, which can have major negative effects on patients. Detecting dangerous illnesses connected to the skin organ, particularly malignancy, requires the identification of pigmented skin lesions (Bhuvaneshwari Shetty, 2022). The accuracy of diagnosis and the early proper treatment can minimize and control the harmful effects of skin cancer. Due to the similar shape of the lesion between skin cancer and benign tumor lesions, physicians consume much more time in diagnosing these lesions (Yunendah Nur Fu'adah, 2020)

Further highlighting the need for more precise and reliable technologies for detecting and diagnosing skin lesions is the rising prevalence of skin illnesses like melanoma and other forms of skin cancer. This is crucial for melanoma patients since the disease can spread swiftly if it is not identified and treated at an early stage. Detecting skin lesions can be a challenging process that requires specialized training, attention to detail, and access to specialized diagnostic tools. Additionally, the shortage of dermatologists in some areas makes it difficult for patients to receive timely and accurate diagnosis and treatment of skin lesions.

This underscores the need for automated methods for skin lesion detection and classification that can be used by healthcare professionals and patients alike. Therefore, the problem statement for skin lesions detection is to develop accurate, objective, and efficient methods fordetecting, classifying, and diagnosing skin lesions to improve patientoutcomes, reduce healthcare costs, and advance medical research.

1.3 Objectives

The objective of this project is as follows:

1. To study the Convolutional Neural Network (CNN) algorithm in the Skin Lesions Detection on human skin.

2. To develop the prototype of Skin Lesions Detection based on Convolutional Neural Network (CNN).

3. To evaluate the accuracy of the Convolutional Neural Network (CNN) algorithm in the Skin Lesions Detection on human skin.

1.4 Project Scope

The scope is limited to the following elements:

User: Skin lesions detection can be used by the patient and dermatologist. The patient can use it to detect if there are any skin lesions disease suffered by the patients while the dermatologist is toconfirm the disease and give the patient an early treatment.

Data: The dataset will be used in skin lesions detection is human skin segmentation dataset. The dataset for this study will be obtained through Kaggle which is a valid source for the database.

Algorithm: The proposed solution for skin lesions detection is the Convolutional Neural Network (CNN) algorithm. CNN algorithm used to classify the data of human skin image using the features extraction. The data will be classified by CNN.

1.5 Project Significance

The project's potential to increase the precision and effectiveness of detecting skin lesions, particularly those that may be cancerous, is what gives it significance for CNN skin lesion detection. Skin cancer is a dangerous, sometimes fatal condition that can be difficult to detect in its early stages. Early diagnosis and treatment, however, can greatly enhance patients' results.

This method has the potential to improve the accuracy of skin lesion detection, allowing earlier and more accurate diagnosis. CNN are deep learning models that are particularly successful at image recognition tasks. Better patient outcomes and quicker treatment may follow from this.

Furthermore, the initiative may be used in a variety of environments, such as telemedicine and remote patient care, when access to dermatologists or other specialists may be restricted. This technology has the potential to increase access to high-quality care and even save lives, making it a huge and important advancement in the healthcare industry.

1.6 Overview of Research Framework

A research framework refers to the overall structure or design of a research study. A well-designed research framework is to ensure that the study produces meaningful and valuable findings. Table 1.1 shows the overview of the research framework.

Table 1.1 Details of Research Framework

PHASE	PRELIMINARY PHASE	DESIGN & IMPLEMENTATION PHASE	EVALUATION PHASE
OBJECTIVE	To study the Convolutional Neural Network (CNN) algorithm in the Skin Lesions Detection on human skin.	To develop the prototype of Skin Lesions Detection based on Convolutional Neural Network (CNN).	To evaluate the accuracy of the Convolutional Neural Network (CNN) algorithm in the Skin Lesions Detection on human skin
ACTIVITIES	• Requirement analysis • Data findings	• Algorithm design • Prototype development	• Testing • Performance evaluation
OUTCOMES	The requirements of Convolutional Neural Network (CNN) method for skin lesions detection.	Skin lesions detection system prototype.	The accuracy and result for skin lesions detection.

1.7 Conclusion

In summary, this chapter included the background research, problem statement, objectives, research scope, and significance of the proposed project. Preliminary research on the project is beneficial. Preliminary research on the project aids in better understanding the issues and workable solutions. The planned project will be discussed in further depth in the following chapter. The Literature Review will be discussed in the following chapter.

CHAPTER 2

LITERATURE REVIEW

This chapter provides an overview of the study's literature review. In order to enhance and apply comprehension of current research and establish familiarity with the study, a literature review is required. This chapter covers image processing, disease detection, skin lesions detection, an overview of Convolutional Neural Network (CNN) algorithm in various problems, similar works and implication of literature review.

2.1 Image Analysis Technique

The development of methods and software for pattern recognition and image processing is moving forward at an unprecedented level. Image Processing and Pattern Recognition give clear overviews of the principles as well as the most recent applications while also containing the most recent modern developments in the field (F. Y. Shih, 2010). Images can be analyzed for content using two main techniques which are image processing and pattern recognition. A collection of computational methods for reconstructing, enhancing, analyzing and compressing images is known as image processing. Pattern recognition is an information-reduction method that involves categorizing visual or logical patterns based on their characteristics and relationships. Pattern recognition phases include measuring the object to find distinguishing properties, extracting features for the defining attributes, and assigning the object to a class based on these features. Image processing and pattern recognition have several uses, including astronomy, medicine, industrial robots, and satellite remote sensing (V. Slamecka, 2023).

2.1.1 Image Processing

Image processing is a technique for converting a physical image into a digital format and applying various operations on it to produce an improved image or extract some relevant information from it. It is a form of signal distribution where the output could be an image or properties related to that image and the input could be an image, such as a video frame or photograph. Typically, an image processing system treats images as two-dimensional signals and then applies pre-established signal processing techniques to them. It is currently one of the technologies with the fastest growth, and it has applications in many different facets of business. Within the fields of engineering and computer science, image processing also serves as a core research subject (Engineers Garage, 2023).

Analogue and digital image processing are the two categories of image processing techniques. For physical copies like prints and images, image processing methods can be analogue or visual. When applying these visual techniques, image analysts employ several interpretational fundamentals. The image processing is not only limited to the area that needs to be researched but also on analyst knowledge. Another crucial element in image processing using visual methods is association. Analysts process images by combining their own knowledge with other data (Engineers Garage, 2023).

There are a few steps in image processing as shown in Figure 2.1, such as image acquisition, image enhancement, image restoration, colour image processing, image compression, segmentation, representation and recognition(Simplilearn, 2023).

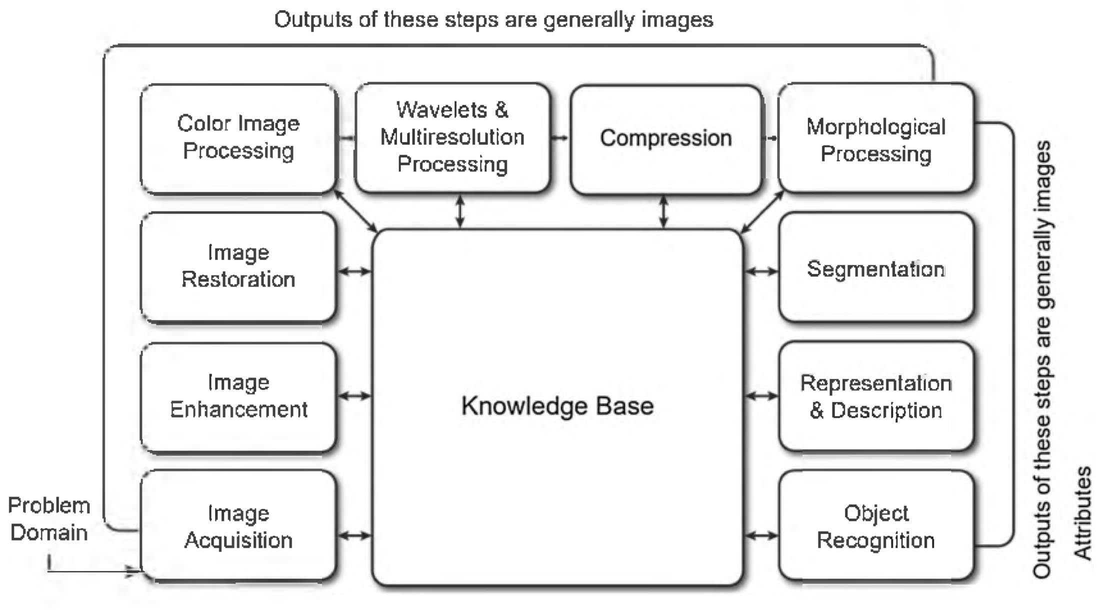

Figure 2.1 Steps in Image Processing

Moreover, image processing types are utilized to manipulate and analyze digital images in a variety of ways. Here are a few common examples such as

- Image Enhancement: Enhance an image's visual impact by adjusting its brightness, contrast, sharpness, or level of noise or artifacts.

- Image Restoration: Recovering or restoring images that have suffered degradation from noise, blurring, or compression.

- Image Filtering: Applying filters to an image to enhance or extract certain elements. This includes methods like sharpening filters or smoothing filters (such as Gaussian blur).

- Image Compression: Reducing an image's size with the least amount of information lost. There are lossless and lossy compression techniques, such as Run-Length Encoding and JPEG, respectively.

- Image Segmentation: Process of dividing an image into separate sections or areas based on the characteristics of the pixels, their color, their texture, or other variables.

- Image Registration: Process of aligning several photographs of the same scene or object to allow for information comparison or fusion.

- Image Morphology: Operations that modify the connectivity, structure, or shape of objects within a picture. Erosion, dilation, opening, and closure are examples of morphological processes.

- Object Recognition: Methods for identifying and recognizing certain items or patterns inside a picture, which frequently involve feature extraction and classification algorithms.

- Image Analysis: Analyzing images to obtain relevant data or insights, such as statistical analysis, object counting, or measurement.

- Image Synthesis: Also known as texture synthesis, image inpainting, or the image reconstruction, is the process of creating new images using data or models that already exist.

These are only a few examples of the different image processing methods that are applied in fields including digital photography, remote sensing, computer vision, and medical imaging. Each technique of image processing serves a different purpose and can be combined to do more complex image modification and analysis activities.

2.2 Disease Detection

Disease detection is the process of determining whether a person or a population has a disease or a health condition. In order to recognize and diagnose diseases at various stages, it involves the use of a variety of methodologies, procedures, and equipment. Early disease detection is the main objective since it enables immediate diagnosis and management, which improves results. The disease can be identified and diagnosed in a number of ways, including through the use of image processing technologies or more conventional methods. Artificial Intelligence (AI) is used by a number of technologies to identify and categorize diseases, including those that identify diseases of the skin, eyes, and nails. The image processing step, which includespicture acquisition, pre-processing, feature extraction, and classification, is used to identify diseases.

2.2.1 Skin Lesions Detection

The process of identifying and analyzing various abnormalities or irregularitieson the skin, such as moles, spots, rashes, ulcers, and other lesions, is known as skin lesion detection. The objective is to identify any early warning indications of potential skin conditions, such as skin malignancies like melanoma, basal cell carcinoma, or squamous cell carcinoma.

Various techniques can be used to detect skin lesions, including automated computer-based analysis, human visual inspection by healthcare experts, or a mix of both. A dermatologist or other healthcare professional can perform this manually or with the use of Computer-Aided Detection (CAD) systems.

Potential skin lesions are discovered by CAD systems using image analysis techniques, which then alert the healthcare professional so that they can be further examined. CAD systems can be used to educate and support patients with skin diseases as well as to increase the accuracy and efficacy of skin cancer screening.

2.3 Deep Learning

A subset of machine learning that involves training artificial neural networks with multiple layers (deep architectures) to learn and make predictions from huge amounts of data is called deep learning. Deep learning models, compared with traditional machine learning models, can automatically develop hierarchical data representations by gradually extracting higher-level features from raw inputs. In a number of fields, including robotics, computer vision, natural language processing, and speech recognition, deep learning has achieved significant results.

CNN is one of the most popular architectures in deep learning, which is highly effective in image and video-related tasks. The Recurrent Neural Network (RNN), which excels at handling sequential input like natural language, is another extensively used design. In a variety of applications, such as image classification, object detection, machine translation, speech recognition, and autonomous vehicles, deep learning has made huge advances. Its success is partially due to its capacity to learn automatically from data, removing the needfor manual feature engineering.

2.3.1 Convolutional Neural Network (CNN)

Machine learning includes Convolutional Neural Networks, also known as convnets or CNNs. It is a subset of the several artificial neural network models that are employed for diverse purposes and data sets. CNN is a particular type of network design for deep learning algorithms that is utilized for tasks like image recognition and pixel data processing.

Although there are different kinds of neural networks in deep learning, CNN is the preferred network architecture for identifying and recognizing objects. They are therefore ideally suited for Computer Vision (CV) activities and for applications where accurate object recognition is crucial, such as facial and self-driving automobile systems.

2.3.2 Overview of Convolutional Neural Network (CNN)

ConvNet, sometimes referred to as the CNN algorithm, is a deep learning algorithm created primarily for processing and analyzing visual input, such as photographs and movies. CNNs have completely changed the field of computer vision and excelled in a number of tasks, such as picture segmentation, object identification, and classification.

CNNs are a subclass of Deep Neural Networks that are frequently used for visual image analysis. CNNs can identify and categorize specific features from images. Their uses include natural language processing, image classification, video and image analysis for medical purposes, and image and video recognition.

CNN is helpful for picture recognition because of its great accuracy. There are many applications for image recognition in several fields, including phone, security, recommendation systems, medical picture analysis, etc.

The CNN is made up of three different kinds of layers as illustrated in Figure 2.2 which has convolutional layers, pooling, and fully-connected (FC). A CNN architecture is created when these layers are stacked. The dropout layer and the activation function, which are detailed below, are two additional crucial parameters in addition to these three layers.

Convolutional Layers : The fundamental components of a CNN are convolutional layers. The input data is processed by a collection of learnable filters, commonly referred to as kernels, in each convolutional layer. By moving over the input, the filters conduct convolutions, extracting regional features and creating feature maps. The number of filters in the layer is correlated with the depth of the feature maps.

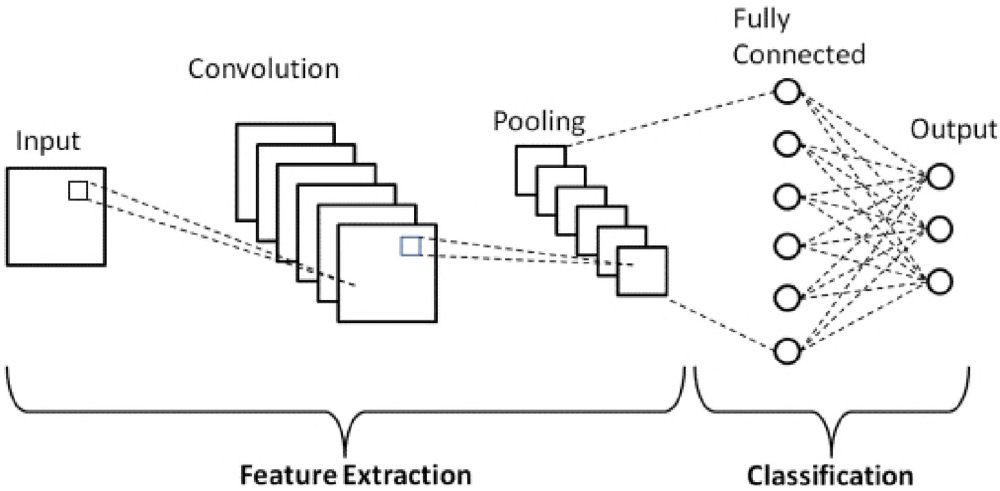

Figure 2.2 CNN Layers

Pooling Layers : By combining layers, the feature maps' spatial dimensions can be reduced while still containing valuable information. Max pooling, the most popular pooling operation, extracts the most value possible within a specified frame. The feature maps can be downscaled with the use of pooling, which also helps to simplify computations and strengthens the model's resistance to changes in input data.

Fully connected Layers : Also called dense layers, fully connected layers in a neural network link every neuron in one layer to every other layer below it. These layers process the previous layers' flattened feature maps and carry out high-level deliberation and decision-making based on the features that were previously learned. For classification tasks, the number of neurons in the final fully connected layer corresponds to the number of classes.

2.4 Implementation of CNN Algorithm in Various Problem

CNN algorithm was implemented in various problems. Table 2.1 below showsthe implementation of CNN in various problems. The first problem is Plant Disease Detection Using based on Deep Convolutional Neural Network that was published in 2022 by J. A. Pandian, V. D. Kumar, O. Geman, M. Hnatiuc, M. Arif, K. Kanchanadevi. The problem of this project is manual monitoring of plant diseases will not give accurate outcomes regularly. Additionally, finding domain experts for monitoring plant diseases is highly difficult and expensive for farmers. Deep Convolutional Neural Network (DCNN) algorithm was used in this project and the result achieved 99.9655% overall classification accuracy, 99.7999% weighted average precision, 99.7966% weighted average recall, and 99.7968% weighted average F1 score.

The second problem is Detection System for Real-time Corn Plant Disease Recognition Deep Convolutional Neural Network based. This project was published by S. Mishra, R. Sachan, D. Rajpal in 2019. The issue of this projectis leaf blight and rust are two of most prevalent diseases causing substantial economic losses to the maize crop in India. If these diseases are identified at an initial stage and remedial measures are taken then crop yield, and grain quality may be preserved. The objective of this project is It is imperative to devise a method that is not only cost-effective and accurate but also deployablein rural areas, resulting in an accuracy of 88.46% demonstrating the feasibilityof this method.

The third problem that implements CNN is detecting Breast Cancer Using Deep Convolutional Neural Networks and Support Vector Machines that was published in 2019 by D. A. Ragab, M. Sharkas, S. Marshall, J. Ren. The problem of this project is that in today's world, the Magnetic Resonance Imaging (MRI) test is done when the radiologists want to confirm the existence of the tumor. The drawback of the Magnetic Resonance Imaging (MRI) is thatthe patient could develop an allergic reaction to the contrasting agent, or that askin infection could develop at the place of injection. It may cause claustrophobia. The objective of this project is to classify breast cancer using deep learning and some segmentation techniques. The result of this project is the accuracy of the new-trained Deep Convolutional Neural Network (DCNN)architecture is 71.01% when cropping the Region Of Interest (ROI) manually from the mammogram. The highest Area Under the Curve (AUC) achieved was 0.88 (88%) for the samples obtained from both segmentation techniques.

The fourth problem is detecting and classifying lung diseases for pneumonia and Covid-19 using Machine and Deep Learning techniques that was published in 2021 by S. Goyal & R. Singh. The problem of this project is it was challenging to differentiate Covid-19 and pneumonia lung diseases for medical experts. The chest X-ray imaging is the most reliable method for lung disease prediction and the objective of this project is to focus on early detection and classification of lung diseases from the raw X-ray images for appropriate treatment using the semi-automated approach for robust feature extraction and deep learning with minimum computation overhead. Deep Learning, Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) was used in this project and resulting accuracy approximately 95% with low computational efforts (approximately 50% of the compared methods).

Lastly, Convolutional Neural Network for Brain Tumor Detection that was published in 2020 by D. C. Febrianto, I. Soesanti, H. A. Nugroho. The problemof this project is that early diagnosis of brain tumors is an essential task in medical work to find out whether the tumor can potentially become cancerous and the objective of this project is to find relevant features of an image to facilitate the classification process. Convolutional Neural Network (CNN) algorithm was used in this project and the result of this project shows that the average accuracy value is 94% and has an average loss value of 0.14181 on thetraining data, but there is a significant difference with the test data results, the average test data accuracy value is 85% and an average loss value of 0.44037.

Table 2.1 Implementation of CNN Algorithm in Various Problem

No.	Title	Year	Problem	Objective	Technique/ Algorithm Method	Result	Reference
1	Plant Disease Detection Using Deep Convolutional Neural Network	2022	Manual monitoring of plant diseases will not give accurate outcomes regularly. Additionally, finding domain experts for monitoring plant diseases is highly difficult and expensive for farmers.	To demonstrate the effectiveness of deep learning, specifically CNNs, in automating and improving the accuracy of plant disease detection. By developing a robust and accurate plant disease detection system, farmers and agricultural practitioners can identify diseased plants early, take timely preventive measures, and minimize crop losses.	Deep Convolutional Neural Network	On the 8850 test images, the proposed DCNN model achieved 99.9655% overall classification accuracy, 99.7999% weighted average precision, 99.7966% weighted average recall, and 99.7968% weighted average F1 score	(J. Arun Pandian, V. Dhilip Kumar, Oana Geman, Mihaela Hnatiuc, Muhammad Arif, K. Kanchanadevi, 2022)
2	Detection and classification of lung	2021	It is challenging to differentiate Covid-19	To focus on early detection and classification of lung	Deep learning, Recurrent Neural	It has been found that the proposed F-RNN-LSTM model provides	(Shimpy Goyal, Rajiv Singh 2021)

	diseases for pneumonia and Covid-19 using machine and deep learning techniques		and pneumonia lung diseases for medical experts. The chest X-ray imaging is the most reliable method for lung disease prediction.	diseases from the raw X-ray images for appropriate treatment using the semi-automated approach for robust feature extraction and deep learning with minimum computation overhead.	Network (RNN) Long Short-Term Memory (LSTM).	better accuracy approximately 95% with low computational efforts (approximately 50% of the compared methods).	
3	Convolutional Neural Network for Brain Tumor Detection	2020	Early diagnosis of brain tumors is an essential task in medical work to find out whether the tumor can potentially become cancerous.	To find relevant features of an image to facilitate the classification process.	Convolutional Neural Network	In the first CNN model, convolution is used, and the average accuracy value is 94% and has an average loss value of 0.14181 on the training data, but there is a significant difference with the test data results, the average test data accuracy value is 85% and an average loss value of 0.44037. In the second CNN model using convolution gets better results, the training data obtained an accuracy value of 96% and a loss value of 0.10046, then the test data	(D C Febrianto, I Soesanti, H A Nugroho, 2020)

						obtained an accuracy value of 93% and a loss value of 0.23264	
4	Deep Convolutional Neural Network based Detection System for Real-time Corn Plant Disease Recognition	2019	Leaf blight and rust are two of most prevalent diseases causing substantial economic losses to the maize crop in India. If these diseases are identified at an initial stage and remedial measures are taken then crop yield, and grain quality may be preserved. Corn disease symptoms at very early stage, manifest on different parts of infected plants, particularly leaves present symptoms of detectable change in colour,	It is imperative to devise a method that is not only cost-effective and accurate but also deployable in rural areas. This paper proposes a deep learning based corn plant disease recognition system that works in a standalone mobile device (Raspberry pi , smart phone)without requiring internet access.	Deep Convolutional Neural Network	During the recognition of corn leaf diseases, the deep learning model achieves an accuracy of 88.46% demonstrating the feasibility of this method	(Sumita Mishra, Rishabh Sachan, Diksha Rajpal, 2019)

			spots and blight. Machine learning techniques have been successful in identification and classification of a wide variety of maize diseases from images of plant leaves.				
5	Breast Cancer Detection Using Deep Convolutional Neural Networks and Support Vector Machines	2019	The magnetic resonance imaging (MRI) is the most attractive alternative to mammogram. However, the MRI test is done when the radiologists want to confirm about the existence of the tumor. The drawback of the MRI is that the patient	For classifying breast cancer using deep learning and some segmentation techniques are introduced. A new computer aided detection (CAD) system is proposed for classifying benign and malignant mass tumors in breast mammography images.	Deep Convolutional Neural Networks and Support Vector Machines	The accuracy of the new-trained DCNN architecture is 71.01% when cropping the ROI manually from the mammogram. The highest area under the curve (AUC) achieved was 0.88 (88%) for the samples obtained from both segmentation techniques.	(Dina A. Ragab, Maha Sharkas, Stephen Marshall, Jinchang Ren, 2019)

			could develop an allergic reaction to the contrasting agent, or that a skin infection could develop at the place of injection. It may cause claustrophobia.				

2.5 Similar Works

Table 2.2 shows the similar work of Skin Lesions Detection System. The first similar work is classification of skin cancer from dermoscopic images using deep neural network architectures. This article was published in 2023 by J. S. M., M P., C. Aravindan and R. Appavu. The problem of this project is skin cancer is normally screened by clinicians through visual examination which is time consuming, error prone and is more subjective. Dermoscopy is a noninvasive imaging technique that eliminates the surface reflection of the skinwhich is able to capture illuminated and magnified images of skin lesions to increase the clarity of the spots. However, the detection of melanoma from dermoscopic images by the dermatologist. The objective of this project is to improve the efficiency and efficacy of skin cancer detection. An automated diagnosis system is necessary to assist clinicians in order to enhance the decision making. The deep convolutional neural network was used in this project. With that, the performance of the proposed system was evaluated using Area under the ROC (Receiver Operating Characteristic) curve (AUC - ROC)and obtained the score of 0.9681 by optimal fine tuning of EfficientNet-B6 with ranger optimizer.

Next, skin lesion classification of dermoscopic images using machine learningand convolutional neural network written by B. Shetty, R. Fernandes, A. P. Rodrigues, R. Chengoden, S. Bhattacharya, K. Lakshmanna and was publishedin 2022. The problem of this project is detecting dangerous illnesses connectedto the skin organ, particularly malignancy, requires the identification of pigmented skin lesions. The objective of this project is to construct a dermascopic skin image recognition system, extract skin lesion features from images. The machine learning and convolutional neural network was used in this project and obtained an accuracy of 95.18% with the Convolutional NeuralNetwork (CNN) model.

Moreover, another similar work is convolutional neural networks for predicting skin lesions of melanoma that was published in 2017 and was written by A. J. Pathiranage. The problem of this project is at the moment, dermoscopy is used as a diagnosis tool to accurately detect the skin lesions ofmelanoma, because if melanoma is diagnosed in its early stages, there is a goodchance of recovery. However, melanoma diagnosis through dermoscopy images is difficult as it requires extensively trained specialists. The objective of this project is, as expertise is in limited supply, systems that can automatically classify skin lesions as either benign or malignant melanoma arevery useful as initial screening tools. Towards this goal, this study presents a convolutional neural network model, trained on features extracted from a highway convolutional neural network pretrained on dermoscopic images of skin lesions. This requires no lesion segmentation nor complex preprocessing. Further, it doesn't cost much computational power to train the model. Convolutional Neural Network was used in this project and this proposed approach achieves a favorable training accuracy of 98%, validation accuracy of 64.57% and validation loss 0.07 in the model with 46% sensitivity and 64%classification accuracy in testing data.

Other than that, detection and classification of skin cancer by using a parallel CNN model that was published in 2020 and was written by N. Rezaoana, M. S. Hossain and K. Andersson are other similar works. The problem of this project is that a dependable automated system for skin lesion recognition is absolutely mandatory in order to minimize effort, time and human life. The objective of this project is to establish a model that diagnoses skin cancer as well as classifies it into various classes through the Convolutional Neural Network. Convolutional Neural Network, image processing and deep learningwas used in this project and the approximately 0.76 weighted average precision, 0.78 weighted average recall, 0.76 weighted average f1-score, and 79.45 percent accuracy are shown by the proposed Convolutional Neural Network (CNN) method.

Furthermore, the last similar work is skin lesion classification using CNN- based transfer learning model. This article was written by K. Dimimiler and B.Sekeroglu and published in 2023. The problem of this project is due to differentappearances of the lesions, there is a limited accuracy in diagnosing melanomas by an expert using visual and clinical inspection. The objective ofthis project is to classify cancerous and non-cancerous skin lesions and all skinlesion types provided in the dataset separately and the designed model increased the classification rates by 20% compared to the conventional CNN. The transfer learning model achieved 0.81, 0.88, and 0.86 mean recall, mean specificity, and mean accuracy in detecting cancerous lesions, and 0.83, 0.90, and 0.86 macro recall, macro precision, and macro F1 score in classifying six skin lesions and the obtained results show the efficacy of transfer learning in skin lesion diagnosis. F1 score is a machine learning evaluation metric that measures a model's accuracy.

Table 2.2 Similar Works of Skin Lesions Detection System

No.	Title	Year	Problem	Objective	Technique/ Algorithm Method	Result	Reference
1	Classification of skin cancer from dermoscopic images using deep neural network architectures	2023	Skin cancer is normally screened by clinicians through visual examination which is time consuming, error prone and is more subjective. Dermoscopy is a noninvasive imaging technique that eliminates the surface reflection of the skin which is able to capture illuminated and magnified images of skin lesions to increase the clarity of the spots. However, the detection of melanoma from dermoscopic images by the dermatologist	To improve the efficiency and efficacy of skin cancer detection an automated diagnosis system is necessary to assist clinicians in order to enhance the decision making.	Deep Convolutional Neural Network	The performance of the proposed system was evaluated using Area under the ROC curve (AUC - ROC) and obtained the score of 0.9681 by optimal fine tuning of EfficientNet-B6 with ranger optimizer.	(Jaisakthi S M, Mirunalini P, Chandrabose Aravindan, Rajagopal Appavu, 2023)

2	Skin Lesion Classification Using CNN-based Transfer Learning Model	2023	Due to different appearances of the lesions, there is a limited accuracy in diagnosing melanomas by an expert using visual and clinical inspection.	To classify cancerous and non-cancerous skin lesions and all skin lesion types provided in the dataset separately.	Convolutional Neural Network	The designed model increased the classification rates by 20% compared to the conventional CNN. The transfer learning model achieved 0.81, 0.88, and 0.86 mean recall, mean specificity, and mean accuracy in detecting cancerous lesions, and 0.83, 0.90, and 0.86 macro recall, macro precision, and macro F1 score in classifying six skin lesions and the obtained results show the efficacy of transfer learning in skin lesion diagnosis.	(Kamil Dimimiler, Boran Sekeroglu, 2023)
3	Skin lesion classification of dermoscopic images using machine learning and convolutional	2022	Detecting dangerous illnesses connected to the skin organ, particularly malignancy, requires the identification of pigmented skin lesions.	To construct a dermascopic skin image recognition system, extract skin lesion features from images.	Machine Learning and Convolutional Neural Network	Obtained an accuracy of 95.18% with the CNN model.	(Bhuvaneshwari Shetty, Roshan Fernandes, Anisha P. Rodrigues, Rajeswari Chengoden, Sweta Bhattacharya, Kuruva Lakshmanna, 2022)

	neural network						
4	Detection and Classification of Skin Cancer by Using a Parallel CNN Model	2020	A dependable automated system for skin lesion recognition is absolutely mandatory in order to minimize effort, time and human life	To establish a model that diagnoses skin cancer as well as classifies it into various classes through the Convolution Neural Network.	Convolutional Neural Network, Image Processing and Deep Learning	Approximately 0.76 weighted average precision, 0.78 weighted average recall , 0.76 weighted average f1-score, and 79.45 percent accuracy are shown by the proposed CNN method.	(Noortaz Rezaoana, Mohammad Shahadat Hossain, Karl Andersson, 2020)
5	Convolutional Neural Networks for Predicting Skin Lesions of Melanoma	2017	At the moment, dermoscopy is used as a diagnosis tool to accurately detect the skin lesions of melanoma, because if melanoma is diagnosed in its early stages, there is a good chance of recovery. However, melanoma diagnosis through dermoscopy images is difficult as it requires extensively trained specialists.	As expertise is in limited supply, systems that can automatically classify skin lesions as either benign or malignant melanoma are very useful as initial screening tools. Towards this goal, this study presents a convolutional neural network model, trained on features extracted from a highway convolutional neural network pretrained on dermoscopic images of skin lesions. This requires no lesion	Convolutional Neural Network	This proposed approach achieves a favorable training accuracy of 98%, validation accuracy of 64.57% and validation loss 0.07 in the model with 46% sensitivity and 64% classification accuracy in testing data.	(Anuruddha Jayasekara Pathiranage, 2017)

				segmentation nor complex preprocessing. Further, it doesn’t cost much computational power to train the model.			

2.6 Implication of Literature Review

This research is focused on an image processing project which is skin lesions detection. The algorithm chosen for skin lesions detection is CNN algorithm. The main goal of this study is to identify the requirements of CNN algorithm in skin lesions detection. According to the previous studies that have been reviewed, CNN algorithm is chosen as the best suitable algorithm to implement and classify in an image processing project due to their ability to efficiently learn hierarchical representations from images, exploit local spatial patterns, and share weights to reduce the number of parameters. CNN algorithm does not require a lot of datasets in this project to get the highest accuracy compared to another algorithm.

CHAPTER 3

METHODOLOGY

This chapter explains the methodology of this research. A research methodology is needed to discuss the details of methodology framework such as the particular approaches or methods employed. It is also covering an overview of the research framework and the details of each phase that are involved in this study.

3.1 Overview of Research Framework

A brief research framework already provided in Chapter 1. In this research framework, there are three phases namely preliminary study phase, design and implementation phase and evaluation phase. The phases will be further separated in this part based on the methods employed in the study.

3.1.1 Detailed of Research Framework

The research framework for this study is detailed in Table 3.1. The research methodology as well as the objectives, tasks to be completed, various activities during the phase, and the results for each phase are included in this table.

Table 3.1 Detailed of Research Framework

Research Methodology/ Phase	**Objective**	**Task**	**Activities**	**Deliverables**
Preliminary Phase	To study the Convolutional Neural Network (CNN) algorithm in the Skin Lesions Detection on human skin.	Literature review	• Requirement analysis • Data findings • Reading articles, blogs and journals about the topic of choice	• Research background • Problem statement • Objectiveness • Significance • Potential methods/techniques • Testing/Evaluation methods
Data Collection		Primary data acquisition	• Collect data from Kaggle and GitHub website	• Do the knowledge acquisition
System Design	To develop the prototype of Skin Lesions Detection based on Convolutional Neural Network (CNN).	Design graphical user interface (GUI)	• Design user interface • Build GUI	• Graphical User Interface design
Implementation		• Writing coding and debugging • System development	• Implement CNN algorithm in Skin Lesions Detection using Convolutional Neural Network • Coding error debugging	• Skin Lesions Detection using Convolutional Neural Network prototype

Evaluation	To evaluate the accuracy on the Convolutional Neural Network (CNN) algorithm in Skin Lesions Detection on human skin.	Test, training and evaluate the accuracy of Skin Lesions Detection using Convolutional Neural Network	• Testing and training Skin Lesions Detection using Convolutional Neural Network • Evaluate accuracy of Skin Lesions Detection using Convolutional Neural Network	• The output of Skin Lesions Detection using Convolutional Neural Network • The accuracy result of the Skin Lesions Detection using Convolutional Neural Network (CNN).

3.2 Preliminary Phase

The first phase of the research framework contains preliminary study where literature review, requirement analysis and data preparation were conducted. This phase is described as an early task to be carried out relevant to the study. The preparation of the project before continuing with the design and implementation phase and evaluating phase. The objective of this phase is to study the requirements of the Convolutional Neural Network (CNN) method as an effective way to detect skin lesions. Several activities were listed down for each task conducted during this phase. At the end of this phase, the understanding of the project and ability to identify the research background, problem statement, objectives, system requirements and data collection.

3.2.1 Literature Review

A literature review is a critical and systematic analysis of the body of knowledge in educational institutions and studies on a particular subject or research question. It involves a thorough examination and analysis of academic publications, articles, research papers, conference proceedings, and other relevant materials that relate to the area of interest. The major goals of a literature review are to give a theoretical basis or the background for a new research study as well as to summarize, evaluate, and synthesize the existing information and findings on the subject. Google Scholar and ResearchGate are just some reliable resources that could be used to gather research papers. The journals, articles, and books can also be found through UiTM EzAccess, an electronic resource subscription service to which UiTM Library hassubscribed. Through this platform, it is provided open access to IEEE Xplore, Scopus, SpringerLink and others. All kinds of journals, articles and books around the world which require subscription or purchase to obtain the information.

The title, area of interest, and associated requirements were fulfilled through reading at the end of this literature study. Many studies that are related to this topic provide information that can be used to select suitable methods and algorithms for this project. Therefore, compared to the similar works that were completed in the chapter before, the information gathered can provide a clearer idea and paths.

3.3 Data Analysis

Analyzing data in a variety of formats is the process of data analysis. Even though there is a lot of data available today, it has spread across many sourcesand comes in diverse formats. All of this data needs to be cleaned up and put into a consistent format for analysis, and data analysis helps with that. Data analysis is crucial to research because it makes data analysis much easier and more precise. It enables researchers to clearly evaluate the data, ensuring that nothing has been left out that could prevent them from making decisions from it (E. Amadebai, 2020).

3.3.1 Data Collection

The process of getting information for study is known as data collection. The dataset needed for this skin lesions detection using CNN is made up of labeled images of skin lesions. The acquired dataset will then be split 80/20, with 80% used for training and 20% for testing as shown in Table 3.2 :

Table 3.2 Data Description of Skin Lesions Detection

Data Type	Secondary Data : Skin Lesions - Dermatoscopic Images Skin Wrinkles Vs Non-Wrinkles
Source	Obtained from Kaggle Website https://www.kaggle.com/datasets/jnegrini/skin-lesions-act-keratosis-and-melanoma https://www.kaggle.com/datasets/rishantrokaha/skin-wrinkles-vs-nonwrinkles
Number of Datasets	300 images Training Datasets : 240 images Testing Datasets : 60 images Ratio : 80:20
Sample of Data	

3.4 System Design

Design phase is the second phase in research methodology. The objective of the phase is to develop a prototype that detects skin lesions using the CNN. It developed the system architecture, flowchart, pseudocode and user interface.

3.4.1 System Architecture

System architecture is a conceptual model that describes the components, connections, behaviour, and high-level structure of a complex system. It functions as a guide for designing, building, and understanding the structure and operation of the system. The complete design of the system, including all of its various subsystems, modules, data flows, interfaces, and connections between them, is represented by the system architecture. The proposed system architecture of Skin Lesions Detection using CNN algorithm was shown in Figure 3.1. User interface and classifying process of the image is included in this system architecture. As the input process, the user will upload the image of the skin. The data acquired will go through the pre-processing process and feature extraction before classification of the image. Through the feature extraction process, the image will extract the important features to classify the image. In the classifying process, the system will read the image before the data processed by the CNN algorithm. CNN algorithm will classify the skin based on specific rules. Then, it will return the user whether the output is detecting skin lesions or normal skin lesions.

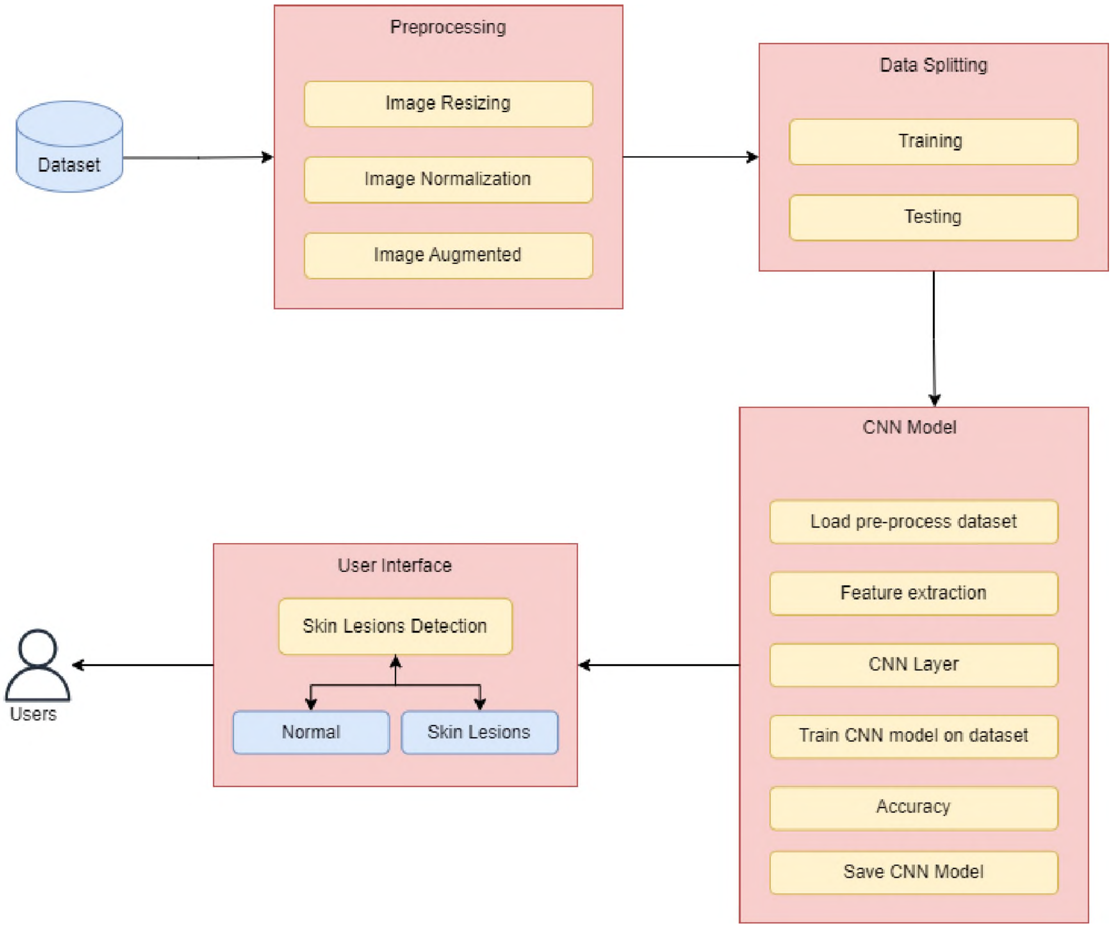

Figure 3.1 System Architecture of Skin Lesions Detection

3.4.2 Flowchart

A flowchart is a graphic representation of a procedure or algorithm that uses various shapes and symbols to represent different steps, decisions and actions sequentially. It works as a visual tool to show how a system or program's processes or activities flow logically. In this study, the flowchart starts out with the user collecting images of human skin. The image inserted will pass through the pre-processing image. Next, the datasets will be split into the ratio of 80:20 for training and testing. Then, the feature extraction process will identify the certain region of the skin image. The result of this process will be used for classification using CNN algorithm. The output of the image will display whether skin lesions disease detected or normal. Figure 3.2 shows the flowchart of skin lesions detection that have been stated in the details earlier.

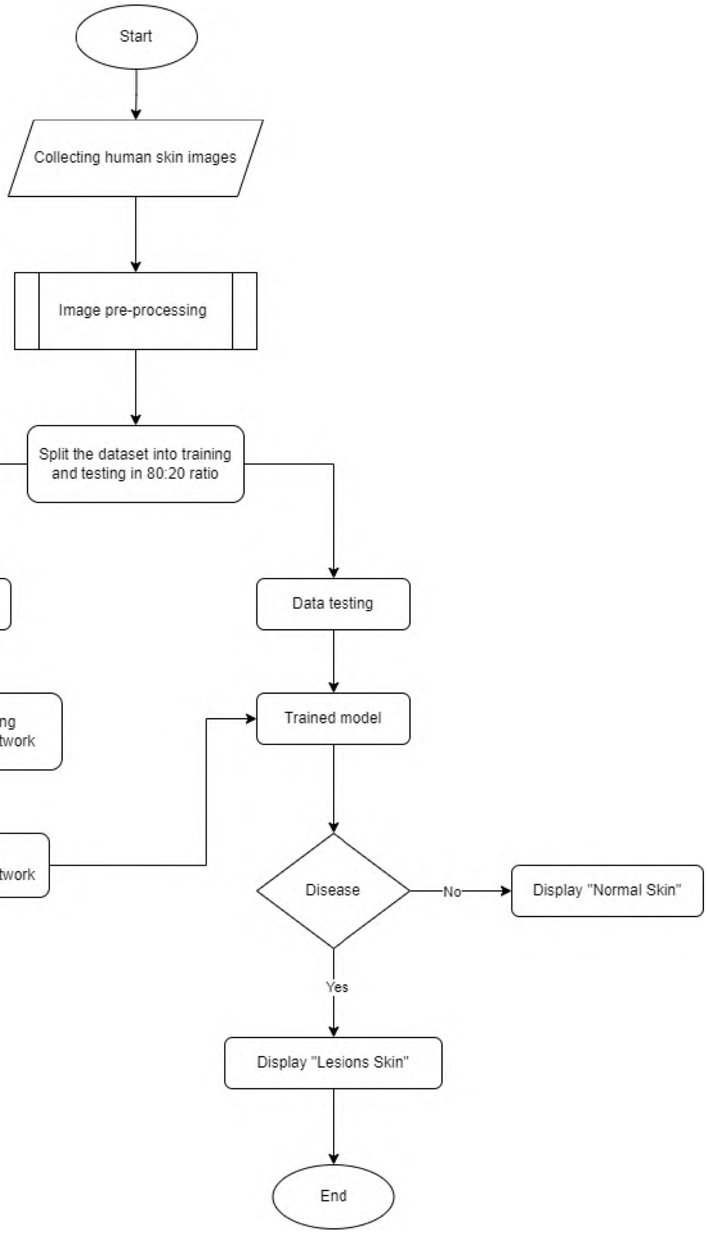

Figure 3.2 Flowchart of Skin Lesions Detection

3.4.3 Pseudocode

In this study, the algorithm chosen is the CNN algorithm due to their ability to effectively capture spatial relationships and hierarchical features within images based on previous chapters. The pseudocode of the algorithm is shown in the Table 3.3 below:

Table 3.3 Pseudocode of Skin Lesions Detection

```
Input :
        Skin lesions test image
Output :
        Skin Lesions Disease Detection

Start
        Read an image from database
        Module Skin Lesions Detection
                Detect the skin of input image
                Pre-process image by reducing noise
                Extract color, shape, and texture of skin from pre-processed image
        Module Skin Lesions Detection
                Divide dataset into training and testing
                Training data sent to CNN for classification
                Match the features with specific characteristics of skin lesions
                Detect the skin lesions
                        If skin lesions is not matched
                                Display “Normal”
                        Else if skin lesions is matched
                                Display “Skin Lesions Disease”
End
```

3.4.4 User Interface Design

GUI stands for Graphical User Interface. It represents the visual user interface, which consists of graphical elements like windows, buttons, menus, and icons, that enables users to interact with applications. GUI is important because it improves the user experience by offering a simple and attractive way of interacting with complicated software systems. As the interface of skin lesions detection, the design is simple and user-friendly. The interface contains a box for the user to upload the image of skin that is needed for detection of skin lesions. Once the detect button is clicked, the process of detecting the skin will start. Then, the result of accuracy and skin lesions detection will display in the text box. Python is used to create this proposed GUI design. Figure 3.3 below shows the interface design of skin lesions detection.

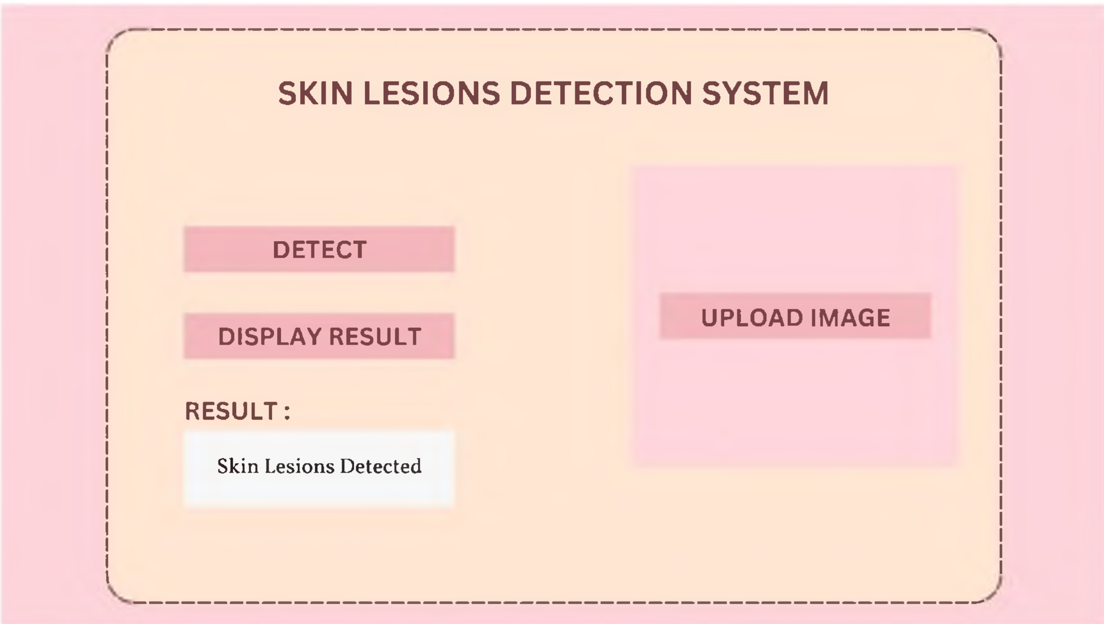

Figure 3.3 GUI Design of Skin Lesions Detection

3.5 System Implementation

The method of ensuring that the information system is operational and satisfies the quality standard is known as system design, which is followed bysystem implementation. The prototype model must go through this step. Python, a high-level programming language, will be used to create thisprototype since it is user-friendly and will be used for overall implementation.

3.5.1 System Requirement

System requirements are the criteria that a platform needs to meet in order for hardware or software to operate effectively and consistently. Before constructing the skin lesions detection prototype, it is necessary to define the system requirements in order to determine the system capacity needed to meet user requests. Issues with setup or operation could happen if the criteria are not met. It is a list of the specifications for hardware and software parts.

The requirements of software and hardware for constructing Skin Lesions Detection systems were identified and installed during this phase. Table 3.4 shows the requirement of hardware for developing skin lesions detection.

Table 3.4 Requirement of Hardware

Characteristic	**Description**
Device	HP LAPTOP-HQK495HJ
Processor	13th Gen Intel(R) Core(TM) i5-1335U 1.30 GHz
Random Access Memory (RAM)	8.00 GB

Software requirements are necessary to implement algorithms in order to construct the system. Table 3.5 shows the requirements of software. Anaconda were used as a programming tool to develop, test and evaluate the system for developing skin lesions detection. It is a free and open-source Python languageas it was the chosen language for developing the system.

Table 3.5 Requirement of Software

Characteristic	**Description**
Operating System	Windows 11 Home Single Language
Programming Tool	Anaconda
Language	Python

3.6 Evaluation Phase

To evaluate the accuracy of the Convolutional Neural Network method in detecting skin lesions, evaluation is required. The goal of this stage is to evaluate whether the CNN algorithm detects skin lesions. The performance of the final system is compared to the initial objective it was designed to achieve, and ongoing testing is done to ensure that the original objective is still being accomplished. This phase has advantages because it allows problems caused by the system's unique circumstances to be corrected before the system is deployed. The task of this phase is completed in order to achieve its goal, which is to evaluate the CNN algorithm's accuracy in identifying skin lesions.

3.6.1 Confusion Matrix

A confusion matrix is a technique for measuring a model's performance that is used in statistical and machine learning classification tasks metric where output can be two or more classes. In Figure 3.4 is the figure of the confusion matrix.

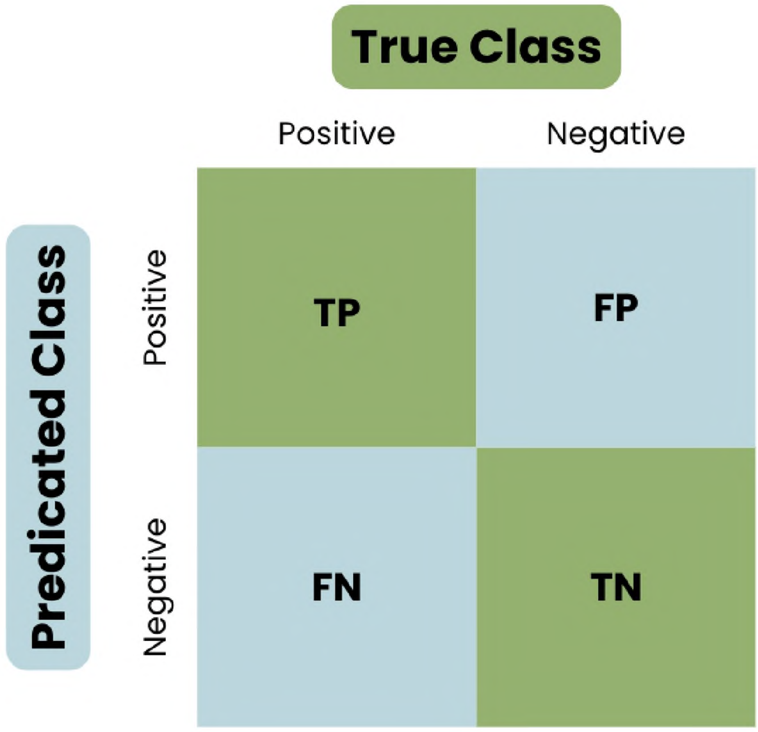

Figure 3.4 Confusion Matrix

- True Positive (TP) - The system correctly predicts skin lesions.
- True Negative (TN) - The system fails to detect skin lesions, classifying them as normal.
- False Positive (FP) - The system incorrectly predicts skin lesions when they are actually normal.
- False Negative (FN) - The system correctly predicts normal skin.

Accuracy is a measure of the overall correctness of the model. It represents the ratio of correctly predicted instances (both true positives and true negatives) to the total number of instances, below is the Equation (1) of the accuracy :

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \tag{1}$$

Next, precision is the ratio of correctly predicted positive observations (true positives) to the total predicted positives (true positives + false positives). It is a measure of the accuracy of the positive predictions. Precision Equation (2) is shown below :

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Recall is the ratio of correctly predicted positive observations (true positives) to the total actual positives (true positives + false negatives). It measures the model's ability to capture all the positive instances in the dataset. Equation (3) of Recall is shown as below :

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \ \text{FN})} \tag{3}$$

The F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall, especially in situations where there is an imbalance between the classes. The F1 score is particularly useful when both false positives and false negatives are important, and you want to avoid favoring one over the other. The equation (4) as shown below :

$$\text{F1} - \text{score} = \frac{2 * (\text{precision} * \text{recall})}{(\text{precision} + \text{recall})} \tag{4}$$

3.7 Gantt Chart

The project timeline's improvement is illustrated in Figure 3.5's Gantt chart. A list of tasks has been arranged based on the phases of the framework's study. The initiative took place over the course of two semesters, and it will continue in semester six next year.

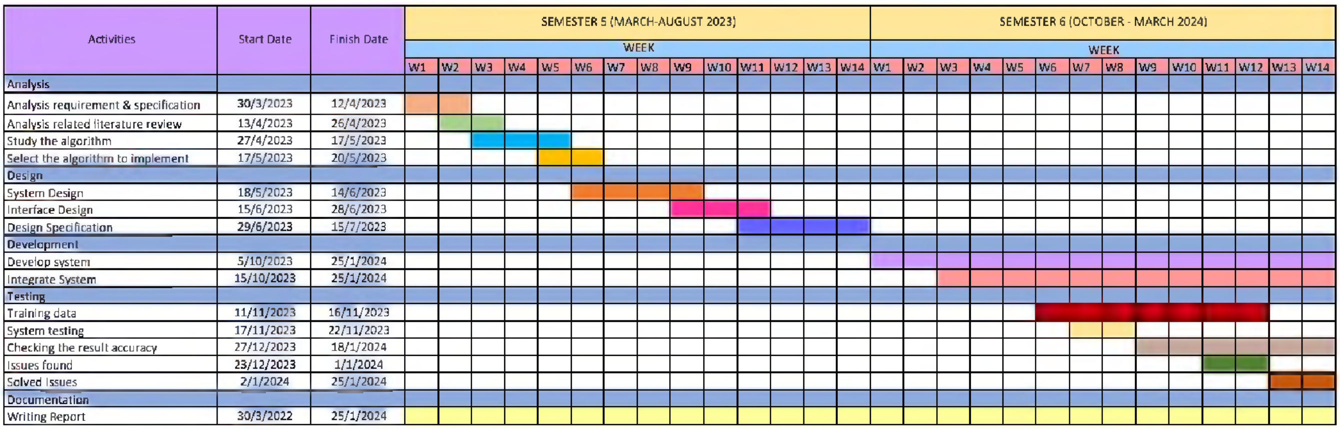

Figure 3.5 : Gantt Chart

3.8 Chapter Summary

In conclusion, there are three main phases in developing skin lesions detection.The phases are preliminary study, design and implementation and evaluation. Each phase consists of different tasks and activities in order to fulfill the development process. This chapter is written as a guideline for the research framework. In this chapter details of system design, system requirements, system implementation and system evaluation are included. The next chapter will discuss the result and findings of the study.

CHAPTER 4

RESULT AND FINDINGS

The findings and outcome of the research will be covered in this chapter. The Skin Lesions Detection System using Convolutional Neural Network results and findings are analyzed and evaluated to ensure that the project adheres to the methodology.

4.1 Conceptual Framework

Figure 4.1 shows the conceptual model framework Skin Lesions Detection using Convolutional Neural Network. The system framework shows that the algorithm used in the current system is known as Convolutional Neural Network.

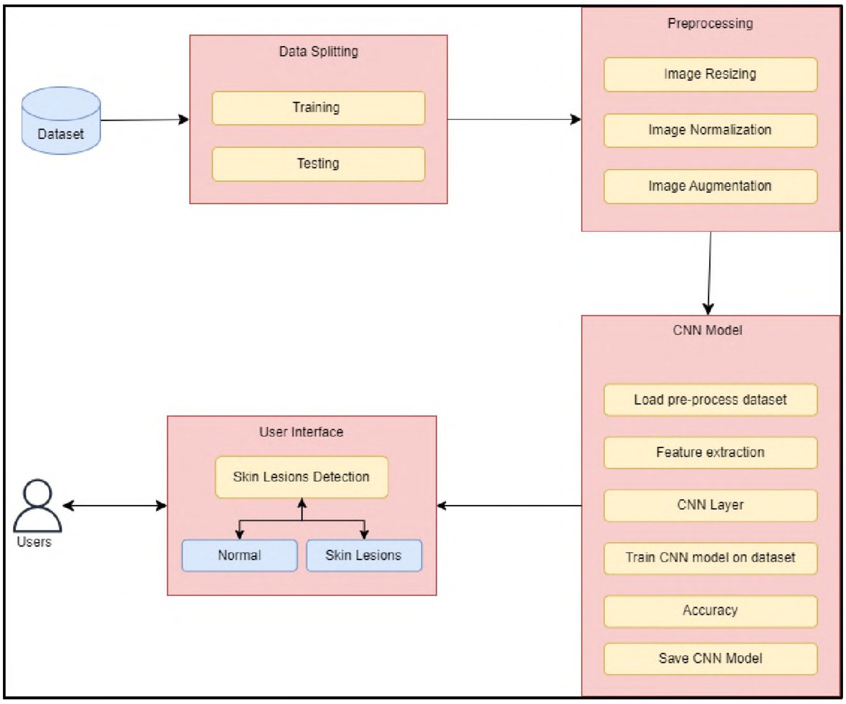

Figure 4.1 System Framework of Skin Lesions Detection

4.2 Program Codes for Convolutional Neural Network

In this program code, the system of Skin Lesions Detection will be developed using Python programming language and Visual Studio Code (VSCode) served as the integrated development environment. Moreover, it will be discussed regarding image pre-processing as well as the Convolutional Neural Network algorithm.

4.2.2 Image Pre-processing

Figure 4.2, Figure 4.3, Figure, 4.4, Figure 4.5 and Figure 4.6 shows the image pre-processing process. Three types of image pre-processing were involved which are image resizing, image normalization and image augmentation.

a. Data Splitting

In image preprocessing, data splitting refers to the practice of dividing a dataset into different subsets for various purposes typically for training, validation and testing. This process is important for assessing the performance of a model and preventing overfitting.

```python
# Create the dataset
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    data_dir,
    validation_split=0.2,
    subset="training",
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size,
    class_names=class_names  # Specify the correct class names
)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    data_dir,
    validation_split=0.2,
    subset="validation",
    seed=123,
    image_size=(img_height, img_width),
    batch_size=batch_size,
    class_names=class_names  # Specify the correct class names
)
```

Figure 4.2 Data Splitting Code

Figure 4.2 shows, the code uses the image_dataset_from_directory function to create TensorFlow tf.data.Dataset objects for the training and validation sets. The validation_split parameter is used to split the dataset into training and validation subsets. The subset parameter specifies whether it is for training or validation. The datasets are configured with specified image dimensions, batch size, and class names. This is a convenient way to load and preprocess image data for training and validation in a deep learning model.

b. Image Resizing

Image resizing is necessary when it need to increase or decrease the total number of pixels. Image resizing process as shown in Figure 4.3 were implemented to ensure consistency in the dimensions of the dataset. This operation was carried out using the PIL (Python Imaging Library) module within the read_and_resize function. The read_and_resize function opens each image file and converts it to the RGB color mode. Moreover, the resize method is applied to adjust the image dimensions to a target size, specified as (224, 224) pixels.

```
# Define a function to read and resize images
def read_and_resize(imname, target_size=(224, 224)):
    try:
        img = Image.open(imname).convert("RGB")
        img = img.resize(target_size, resample=3)  # Use numerical value 3 for ANTIALIAS
        return np.asarray(img)
    except Exception as e:
        print(f"Error processing file {imname}: {e}")
        return None
```

Figure 4.3 Image Resizing Code

c. Image Normalization

Image normalization is the process that changes the range of pixel values to bring image to range that is normal to sense. The data is usually scale to a fixed range from 0 to 1. Pixel values were normalized by dividing each pixel by the maximum pixel value (255) as illustrated in Figure 4.4 :

```
#To prevent overfitting
X_train = X_train/255.
X_test = X_test/255.
```

Figure 4.4 Pixel Values Normalization Code

Additionally, in the Figure 4.5 the preprocessing.normalize function were utilized from the scikit-learn library to normalize non-image features. This function scales each feature to have unit norm, ensuring that the data lies on the unit hypersphere. In the provided example, the x_array was normalized using this function.

```
from sklearn import preprocessing
import numpy as np
x_array = np.array([2,3,5,6,7,4,8,7,6])
normalized_arr = preprocessing.normalize([x_array])
print(normalized_arr)
```

Figure 4.5 Image Normalization Code

d. Image Augmentation

Moreover, image augmentation was involved in this code as shown in Figure 4.6. It is to increase the variety of the training dataset, thereby improving the model's generalization performance. Three data augmentation layers are added sequentially which are RandomFlip("horizontal"), RandomRotation(0.1), and RandomZoom(0.1).

```
data_augmentation = keras.Sequential(
  [
    layers.experimental.preprocessing.RandomFlip("horizontal",
                                                 input_shape=(img_height,
                                                              img_width,
                                                              3)),
    layers.experimental.preprocessing.RandomRotation(0.1),
    layers.experimental.preprocessing.RandomZoom(0.1),
  ]
)
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```

Figure 4.6 Image Augmentation Code

For each iteration, an augmented image is generated using the data_augmentation' model as illustrated in Figure 4.7. The result is a 3x3 grid of original and augmented images, illustrating how the data augmentation layers modify the appearance of the input images.

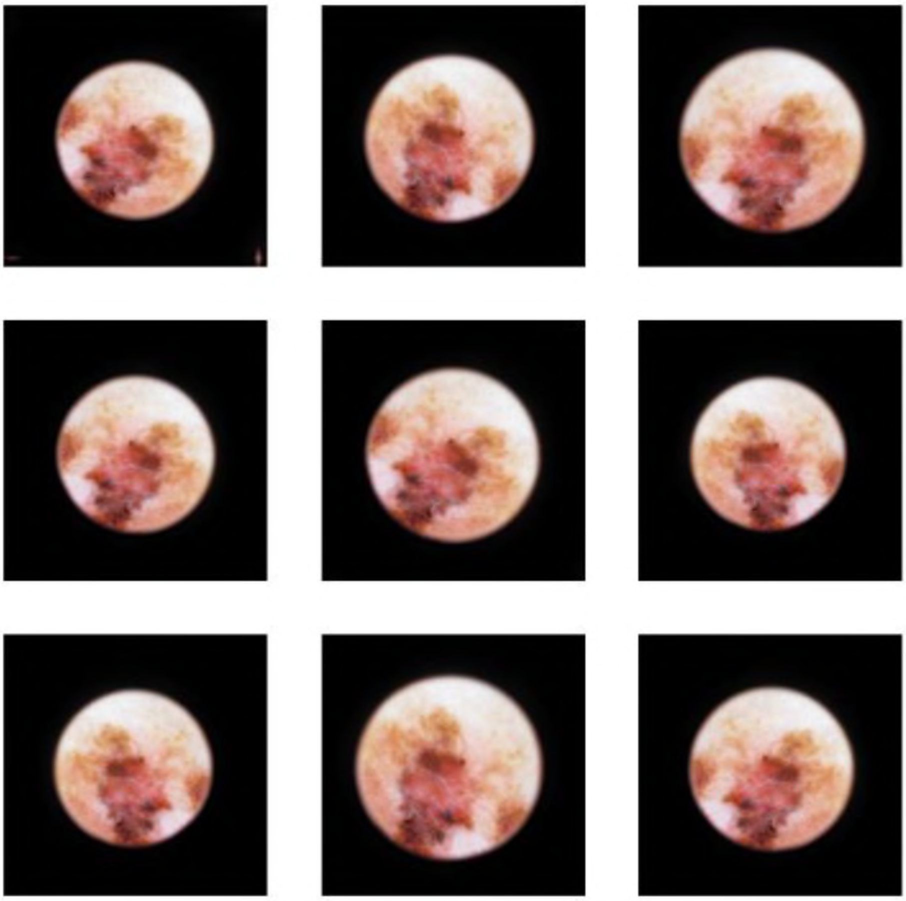

Figure 4.7 Output for Image Augmentation

4.2.3 Convolutional Neural Network Model

The main algorithm that is used in this system is Convolutional Neural Network (CNN). Figure 4.8 shows lines that import various modules from Keras, which is a high-level neural networks API. These modules are essential for building and training neural network models.

```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPool2D, Flatten, Dense, Dropout, BatchNormalization
from keras.optimizers import Adam
from keras.preprocessing.image import ImageDataGenerator
from keras.initializers import he_normal
from keras.callbacks import EarlyStopping
```

Figure 4.8 CNN Keras Modules Code

In Figure 4.9, the sequential models are initialized. Various layers were added such as CNN layers, batch normalization, max pooling and dropout and fully connected layers are added sequentially to create the architecture of the CNN. The final layer is a dense layer with a single neuron and sigmoid activation, indicating binary classification.

```
model = Sequential()

# Convolutional Layer
model.add(Conv2D(filters = 32,
                kernel_size = (3,3),
                input_shape = (32, 32, 3 ),
                activation = 'relu',
                padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())

# Pooling layer
model.add(MaxPool2D( pool_size = (2,2)))

# Dropout Layer
model.add(Dropout(0.25))


model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())

model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(0.25))


model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())

model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

# Flattening
model.add(Flatten())

# Fully connected layers
model.add(Dense(128, activation = 'relu'))
model.add(Dropout(0.25))
#model.add(Dense(10, activation = 'softmax'))
model.add(Dense(1, activation = 'softmax'))

model.summary()
```

Figure 4.9 Layers of CNN Algorithm

Next, Figure 4.10 shows the model summary for the algorithm.

```
Model: "sequential_167"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_264 (Conv2D)         (None, 32, 32, 32)        896

 batch_normalization_263 (B  (None, 32, 32, 32)        128
 atchNormalization)

 conv2d_265 (Conv2D)         (None, 32, 32, 32)        9248

 batch_normalization_264 (B  (None, 32, 32, 32)        128
 atchNormalization)

 max_pooling2d_137 (MaxPool  (None, 16, 16, 32)        0
 ing2D)

 dropout_238 (Dropout)       (None, 16, 16, 32)        0

 conv2d_266 (Conv2D)         (None, 16, 16, 64)        18496

 batch_normalization_265 (B  (None, 16, 16, 64)        256
 atchNormalization)

 conv2d_267 (Conv2D)         (None, 16, 16, 64)        36928
...
Total params: 1865249 (7.12 MB)
Trainable params: 1863329 (7.11 MB)
Non-trainable params: 1920 (7.50 KB)
```

Figure 4.10 Summary of the CNN Algorithm

4.3 User Interface

As shown in Figure 4.11 is the graphical user interface for this system. Tkinter is the standard GUI (Graphical User Interface) toolkit for the Python programming language. Set of tools and libraries is provided to create graphical user interfaces for desktop applications. Tkinter is widely used due to its simplicity and integration with Python.

```
import tkinter as tk
```

Figure 4.11 Tkinter Module Code

The modified model in Figure 4.12 is loaded without compilation. Then, the SkinLesionDetectorGUI class is defined, which represents the graphical user interface for the skin lesion detector.

```
## Load the modified model without compiling
model_path = modify_model('saved_model_h5/my_model.h5')
model = tf.keras.models.load_model(model_path, compile=False)
```

Figure 4.12 GUI Model

Figure 4.13 shows the code of upload_image method uses Tkinter's filedialog to prompt the user to select an image file. If a file is selected, the image is opened, displayed on the canvas, and the skin type is determined based on the folder structure.

```
def upload_image(self):
    file_path = filedialog.askopenfilename(filetypes=[("Image files", "*.png;*.jpg;*.jpeg")])
    if file_path:
        self.image = Image.open(file_path)
        self.display_image()

        # Determine the skin type based on the folder
        self.skin_type = self.get_skin_type(file_path)
```

Figure 4.13 Upload Image

The detect_skin method preprocesses the uploaded image is shown in Figure 4.14, makes a prediction using the loaded model, and displays the result on the GUI. The result is determined based on a probability threshold.

```
def detect_skin(self):
    if hasattr(self, 'image'):
        preprocessed_image = self.preprocess_image(self.image)
        prediction = model.predict(preprocessed_image)
        probability_scores = prediction[0]

        # Set a threshold for normal skin detection
        threshold = 0.5  # Adjust as needed

        # Display the result on the GUI
        if probability_scores[1] >= threshold:
            result = "Lesion Skin"
        else:
            result = "Normal Skin"

        # Update the result label within the progress bar
        self.result_label.config(text=result)
        self.progress_bar["value"] = 100  # Set progress bar to 100%

    else:
        self.result_label.config(text="Please upload an image first.")
```

Figure 4.14 Detecting Skin Type

The GUI has a window with a title "Skin Lesion Detector" and a pastel pink background as illustrated in Figure 4.15. It consists of various widgets, including labels, buttons, a canvas for image display, and a progress bar. Widgets are configured with colors, fonts, and dimensions to create an aesthetic appearance. In this GUI there is a function upload image for image detection process and after the image was input into the system, then the system will process the image and display the result of the test image.

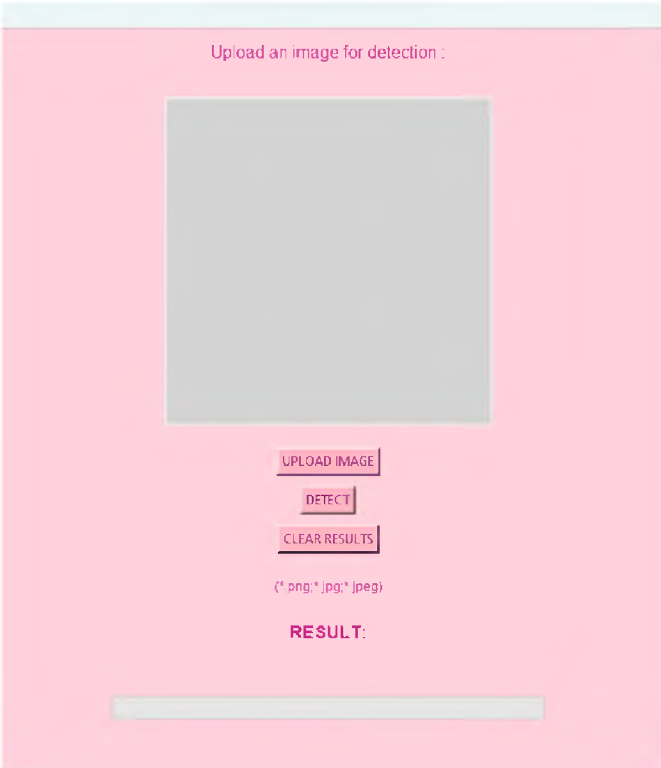

Figure 4.15 GUI of Skin Lesions Detection System

4.4 Accuracy Testing

Figure 4.16 below shows the coding to specify how many lines will be printed and which number of epochs to train the dataset. In the code also have time function to state how long the training will take time to be completed.

```
Epoch 1/10
10/10 [==============================] - 1s 10ms/step - loss: 0.4750 - accuracy: 0.8200
Epoch 2/10
10/10 [==============================] - 0s 7ms/step - loss: 0.3740 - accuracy: 0.8867
Epoch 3/10
10/10 [==============================] - 0s 7ms/step - loss: 0.3111 - accuracy: 0.8900
Epoch 4/10
10/10 [==============================] - 0s 7ms/step - loss: 0.2682 - accuracy: 0.8967
Epoch 5/10
10/10 [==============================] - 0s 8ms/step - loss: 0.2064 - accuracy: 0.9000
Epoch 6/10
10/10 [==============================] - 0s 7ms/step - loss: 0.1719 - accuracy: 0.9433
Epoch 7/10
10/10 [==============================] - 0s 8ms/step - loss: 0.1315 - accuracy: 0.9567
Epoch 8/10
10/10 [==============================] - 0s 7ms/step - loss: 0.1067 - accuracy: 0.9700
Epoch 9/10
10/10 [==============================] - 0s 8ms/step - loss: 0.0910 - accuracy: 0.9700
Epoch 10/10
10/10 [==============================] - 0s 8ms/step - loss: 0.0876 - accuracy: 0.9767
10/10 [==============================] - 0s 3ms/step
```

Figure 4.16 Part of Training Accuracy

After the training has been completed, there is Figure 4.17 that shows the testing the dataset.

```
Epoch 1/10
1875/1875 [==============================] - 17s 8ms/step - loss: 0.8957 - accuracy: 0.7051 - val_loss: 0.3783 - val_accuracy: 0.8762
Epoch 2/10
1875/1875 [==============================] - 15s 8ms/step - loss: 0.4508 - accuracy: 0.8566 - val_loss: 0.2197 - val_accuracy: 0.9266
Epoch 3/10
1875/1875 [==============================] - 15s 8ms/step - loss: 0.3344 - accuracy: 0.8940 - val_loss: 0.1612 - val_accuracy: 0.9472
Epoch 4/10
1875/1875 [==============================] - 15s 8ms/step - loss: 0.2704 - accuracy: 0.9144 - val_loss: 0.1409 - val_accuracy: 0.9536
Epoch 5/10
1875/1875 [==============================] - 16s 9ms/step - loss: 0.2284 - accuracy: 0.9277 - val_loss: 0.1155 - val_accuracy: 0.9612
Epoch 6/10
1875/1875 [==============================] - 16s 8ms/step - loss: 0.1995 - accuracy: 0.9373 - val_loss: 0.1011 - val_accuracy: 0.9673
Epoch 7/10
1875/1875 [==============================] - 15s 8ms/step - loss: 0.1783 - accuracy: 0.9438 - val_loss: 0.0900 - val_accuracy: 0.9697
Epoch 8/10
1875/1875 [==============================] - 15s 8ms/step - loss: 0.1584 - accuracy: 0.9511 - val_loss: 0.0981 - val_accuracy: 0.9679
Epoch 9/10
1875/1875 [==============================] - 15s 8ms/step - loss: 0.1468 - accuracy: 0.9534 - val_loss: 0.0852 - val_accuracy: 0.9726
Epoch 10/10
1875/1875 [==============================] - 16s 8ms/step - loss: 0.1357 - accuracy: 0.9571 - val_loss: 0.0881 - val_accuracy: 0.9706
313/313 [==============================] - 1s 3ms/step - loss: 0.0881 - accuracy: 0.9706
Test Accuracy: 0.9706000089645386
```

Figure 4.17 Part of Testing Accuracy

Figure 4.18 shows the confusion matrix of skin lesions detection system using convolutional neural network. The classifier has 98% accuracy, 91% for precision, 94% for recall and 93% for F1-score.

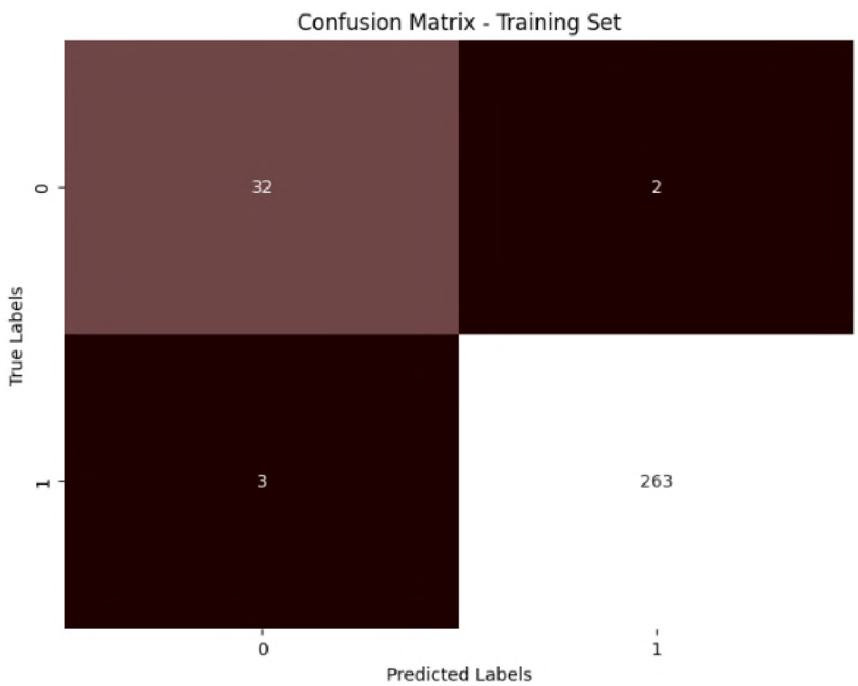

Figure 4.18 Confusion Matrix

Figure 4.19 shows the classification report of skin lesions detection using convolutional neural network. The report is for a binary classification problem with

Normal and Lesions as classes. The precision for each class is reported in the "precision" column, which is the ratio of true positive predictions to all positive predictions (TP + FP). The "recall" column shows the recall for each class, which is the ratio of true positive predictions to total positive cases (TP + FN). The column "f1-score" displays the F1 score, which is the harmonic mean of precision and recall and provides a single number that summarizes the classifier's performance. Finally, the "support" column shows how many samples are in each class. The report also summarizes the classifier's overall performance by reporting the "accuracy," "macro avg," and "weighted avg" of precision, recall, and F1 score. The "accuracy" is defined as the proportion of correct predictions to total number of samples. The "macro avg" is the unweighted average of the metrics across all classes, giving each class equal weight regardless of size. The "weighted avg" is the average of the metrics weighted by support, giving more weight to metrics from the larger class.

Classification Report - Training Set:

	precision	recall	f1-score	support
Normal	0.91	0.94	0.93	34
Lesions	0.99	0.99	0.99	266
accuracy			0.98	300
macro avg	0.95	0.96	0.96	300
weighted avg	0.98	0.98	0.98	300

Figure 4.19 Classification Report

4.5 Result and Analysis

The result and analysis section are crucial for conveying the main findings of a study and demonstrating the researcher's understanding of the data collected. Simulation of the project system is actually a system demonstration. Based on the project, the system will detect of human skin image to recognize whether it has skin lesions or not. Convolutional neural network algorithm is used in this system for the detection. Figure 4.20 below is the output graphical user interface in this system. As shown below, the input image is human skin that, and the result came out is normal skin. Thus, normal skin typically appears smooth, uniform in color, and without any obvious abnormalities. It may vary in color depending on factors such as ethnicity, sun exposure, and individual characteristics.

Figure 4.20 Output of Skin Lesions Detection System (Normal Skin)

While Figure 4.21 below is the output graphical user interface in this system for the result output of lesion skin. Moreover, lesions refer to any abnormality or damage in the skin, which can manifest in various forms such as bumps, sores, ulcers, discoloration, or irregular growths and it may vary in size, shape, color as well as the texture depending on their underlying cause.

Figure 4.21 GUI of Skin Lesions Detection System

4.5.1 Evaluation of CNN Model

Achieving the main objective of the skin lesions detection system requires testing its accuracy, which is the most crucial phase. The system's efficacy is measured by the classification accuracy parameter. The accuracy of the suggested structure for applying convolutional neural networks (CNNs) to the identification of skin lesions was evaluated through four different tests. Next, the middle accuracy value was computed for each testing and instruction division. There are two ways to split the data: the first splits it into 70% for training and 30% for testing, while the second splits it into 80% for training and 20% for testing. As part of the final method, 90% of the data will be used for training and 10% for testing.

The greatest outcomes are produced by training and testing techniques that allocate 10% for testing and 90% for teaching, as Table 4.1 illustrates. These results demonstrate the amount of data utilized for training. The testing accuracy was assessed at the conclusion of every training session. The accuracy of the training and testing split ratios for 80:20, 70:30, and 90:10 is also shown.

Table 4.1 Training and Testing Dataset Split

No.	Data Split	Epoch	Database Split		Accuracy
			Percentage (%)	**Total Data**	
1	• Training • Testing	10 10	80% 20%	240 60	97% 98%
2	• Training • Testing	10 10	70% 30%	210 90	100% 99%
3	• Training • Testing	10 10	90% 10%	270 30	89% 87%

The comparison of several training and testing epochs for each ratio for the human skin image is displayed in Table 4.1. There were 300 of human skin images were used. Each ratio’s complete dataset was divided correspondingly.

4.6 Conclusion

In conclusion, all the phases that are involved in the system development has been completed successfully based on the conceptual model framework to make sure the system that was build can function well. In this chapter there is also an evaluation for this project which is the confusion matrix and classification report. The CNN model has a good performance as it potentially improves the accuracy and efficiency of detecting skin lesions, allowing for early treatment.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

This chapter will elaborate on the overall explanation of this research and wraps up what has been discussed in previous chapters. All previous chapters, including the introduction, literature review, research methodology, results and findings, are summarized and thoroughly explained. This chapter began with a project summary, study contribution, study limitations and future work recommendations.

5.1 Project Summary

The first chapter of this study provides an overview as well as a detailed explanation of what will be done in this study. The problem statement is stated and explained in the first chapter. The understanding of the problem statements leads to the acquisition of the objective. To solve this problem, a machine learning method which is deep learning called Convolutional Neural Network (CNN) algorithm is used.

Next, literature review is involved in the second chapter of the study. In the second chapter, a detailed explanation on how image processing and the convolutional neural network algorithm work was included. This chapter also contains a detailed explanation of skin lesions.

Other than that, for the third chapter which is the research methodology. This chapter explains the entire research process. Three phases of research process that was explained in this chapter are preliminary phase, design and implementation phase and evaluation phase. The step-by-step process to build this skin lesions detection system using Convolutional Neural Network was explained in detail in this chapter.

Moreover, the fourth chapter is regarding the result and findings. In this chapter, all the results and findings for this skin lesions detection system using Convolutional Neural Network are stated.

The fifth chapter is the last chapter in this research which is conclusion and recommendation. This chapter is all about the project summary, project contributions, project limitations and also the future work recommendation.

As for the system, this system managed to accomplish its three objectives successfully. Firstly, the objective is to study the convolutional neural network algorithm in the skin lesions detection on human skin. This objective was achieved by doing the research about the algorithm in various sources such as articles, blogs, websites, and journals. The algorithm that has been used to implement in this project is the convolutional neural network.

Besides that, the second objective is to develop the prototype of skin lesions detection based on convolutional neural network. This objective involves in designing and developing the system prototype.

Third, to evaluate the accuracy on the convolutional neural network algorithm in skin lesions detection on human skin. After evaluating the algorithm by using confusion matrix to calculate the accuracy, precision, recall and F1-score. This mean that the objective was successfully achieved.

5.2 Project Contribution

The research on the detection of skin lesions using Convolutional Neural Network (CNN) contributes to the field of medical image analysis by introducing a novel method for detecting skin lesions using human skin. CNNs are ideal for image classification and have demonstrated promising results in a variety of medical image analysis task. The study intends to improve the accuracy of skin lesions detection by employing CNNs.

5.3 Project Limitations

Project limitations refer to factors that can affect the scope, implementation or outcomes of the project. It may arise from various sources and essential to identify and acknowledge them to provide a clear understanding of the project's boundaries. The limitations are limited dataset size because the CNN model may struggle to generalize well to unseen data. Next, inaccurate or inconsistent labeling of lesions in the dataset may also impact the model's training and evaluation.

5.4 Future Work Recommendation

For future work recommendation, this system can use larger Datasets to train and validate the CNN, collect and use larger and more diverse datasets of human skin images. This will ensure the model's generalizability across different populations. Next, investigate transfer learning techniques to leverage pre-trained models on large datasets. It will potentially be reducing the need for extensive labeled data.

5.5 Conclusion

In conclusion, this project successfully developed a skin lesion detection system using CNN with a remarkable accuracy rate of 98%. The findings indicate the potential of CNN-based approaches in automated skin lesion diagnosis, offering significant benefits in terms of efficiency and accuracy compared to traditional methods. The achievement of such high accuracy underscores the effectiveness of CNNs in analyzing complex visual data like skin lesion images. However, further research is warranted to explore enhancements such as fine-tuning model architectures, incorporating additional data sources, and addressing class imbalances to further improve the performance of the system.

Overall, this project contributes to the advancement of computer-aided diagnosis systems in dermatology, with the potential to revolutionize the way skin lesions are detected and diagnosed, ultimately leading to improved patient outcomes and healthcare delivery.

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