DEEP CONVOLUTIONAL NETWORK FOR CANCER TYPE IDENTIFICATION

A project work submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology In Electronics and Communication Engineering

Submitted by

N.Abhinaya (319126512166) M.V.S.K.Vamsi(320126512L18)

A.Manasa (319126512129) K.Yeswanth Kumar(320126512L24)

Under the guidance of

Dr. J. Bhaskhar Rao, Associate Professor

B.Jena, Assistant Professor

ECE Department

Department of Electronics and Communication Engineering

ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES

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Sangivalasa, Bheemili Mandal, Visakhapatnam dist.(A.P)

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Sangivalasa, Bheemili Mandal, Visakhapatnam dist.(A.P)

PRAGNANAM BRAHMA

ANITS

CERTIFICATE

This is to certify that the project report entitled " **Deep Convolutional Neural Network for Cancer Type Identification** " submitted by N.Abhinaya (319126512166) , M.S.V.K Vamsi (320126512L18), A.Manasa (319126512129), K.Yeswanth Kumar (320126512L24) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Department of Electronics and Communication Engineering of Anil Neerukonda Institute of Technology and Sciences (A), Visakhapatnam is a record of bonafide work carried out by us.

Under the guidance of

B.Jena

Assistant Professor

Dept. of ECE, ANITS

Assistant Professor
Department of E.C.E.
Anil Neerukonda
Institute of Technology & Sciences
Sangivalasa, Visakhapatnam-531 162

Head of the Department

Dr.B. Jagadeesh

Professor &HoD

Dept. of ECE, ANITS

Head of the Department
Department of E C E
Anil Neerukonda Institute of Technology & Sciences
Sangivalasa - 531 162

DECLARATION

We, **N.Abhinaya (319126512166) , M.S.V.K Vamsi (320126512L18), A.Manasa (319126512129), K.Yeswanth Kumar (320126512L24)** of Fourth Year B.Tech., in the Department of Electronics and Communication Engineering from ANITS, Visakhapatnam, here by declare that the project work entitled "**Deep Convolutional Neural Network for Cancer Type Identification** " is carried out by us and submitted in partial fulfillment of the requirements for the award of Bachelor of Technology in Electronics and Communication Engineering , under Anil Neerukonda Institute of Technology & Sciences(A) during the academic year 2022-2023 and has not been submitted to any other university for the award of any kind of degree.

PROJECT STUDENTS

N.Abhinaya (319126512166)

M.S.V.K Vamsi (320126512L18)

A.Manasa (319126512129)

K.Yeswanth Kumar (320126512L24)

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PROJECT STUDENTS

N.Abhinaya (319126512166)

M.S.V.K Vamsi (320126512L18)

A.Manasa (319126512129)

K.Yeswanth Kumar (320126512L24)

ABSTRACT

Cancer is one of the present common causes for death in the world. The early recognition of the cancer and developing the new treatment techniques has been essential. The purpose of this project is to identify the type of cancer and provide information for the growing new techniques in treatment. The earlier we identify the easier the treatment could be. The trending and most reliable technique to follow in this identification is usage of Convolution neural network (CNN).

Datasets of the required digital images are to be provided in this proposal model which helps in identifying the linear and non linear information from the input data. The required methodology also follows the mathematical and probabilistic formulae. In this model, training is provided at the beginning and followed by testing because any failure may lead to poor performance. The adaptive techniques help in improving the performance. Experimental result which is expected to show that our project can achieve required identification accuracy in an early stage.

KEYWORDS: Cancer detection, Convolutional neural network, training and testing datasets, digital images, probabilistic.

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CHAPTER 1

INTRODUCTION

1. INTRODUCTION

The subject area known as "medical image analysis" focuses on creating tools and algorithms for the interpretation of medical pictures such as X-rays, CT scans, MRIs, ultrasounds, and others. The aim of medical image analysis is to extract useful information from medical images that can assist in the diagnosis, treatment, and monitoring of various diseases and medical conditions.

Image preprocessing, segmentation, feature extraction, and classification are some of the phases involved in medical image analysis. Images are first cleaned and improved during the image preprocessing stage to get rid of noise and other artifacts that could compromise the precision of later studies. Segmentation involves identifying regions of interest in the image, such as tumors or organs, and separating them from the surrounding tissue.

Many different medical specialties, including radiology, oncology, cardiology, and neurology, can benefit from the use of medical image analysis. In this model, it has been applied to the early identification of cancer. Different approaches have been put forth in 2012, 2015, and 2017. DenseNet has significantly outperformed the most benchmark tasks when compared to the state-of-the-art CNN, and it has excelled in numerous applications like image recognition.

The use of deep convolutional networks (CNNs) in a variety of applications, such as speech and picture recognition, has been shown effective. CNNs have recently been used to identify the type of cancer from medical imaging, like computed tomography scanned images.

Identifying the type of cancer is important because it enables more precise diagnosis and therapy planning. The optimal course of therapy, including the most potent drugs and therapies, can be decided upon by doctors with the support of a patient's individual cancer kind. A CNN may be trained to recognise patterns and features unique to each form of cancer by exposing it to a huge dataset of medical images. Deep learning models for cancer type detection can help to lessen the workload of medical personnel as well as assist in diagnosis and therapy planning. Doctors and pathologists may concentrate on other crucial activities, such as creating treatment plans and caring for patients, by automating the process of detecting cancer kinds.

Dermoscopy is a non-invasive diagnostic method used in dermatology to obtain large images of the skin for diagnosis. Dermoscopy images, also known as dermoscopy images or dermoscopy images, are important in dermatology for many reasons.

Dermoscopy images give the dermatologist a better view of the skin, allowing features that cannot be seen with the naked eye. This aids in the early detection and detection of skin cancers that are difficult to detect with the naked eye alone, such as melanoma.

Data is information collected and organized for a specific purpose. Data can be of many types, such as structured data, unstructured data, or both. Data is often used in machine learning and data science to teach models or test algorithms. This database consists of snapshots and is often used in computer vision applications such as object detection or face recognition.

The typical pipeline for cancer type identification using CNNs involves the following steps:

1. Preliminary data: Medical images (mammograms, CT scans, dermoscopic images, etc.) are first used to remove noise, normalize density and change the length of the image.
2. Feature extraction:CNNs are used to extract relevant features from pre-processed images. Generally, CNNs are pre-trained on large datasets such as ImageNet and leverage clinical data to improve performance.
3. Classification:The extracted features are fed into a matching algorithm used to classify the image into one of the different cancer types.

Here are some general steps for building a deep convolutional network for cancer type Identification:

- Dataset collection: Collect large and diverse clinical data across cancer types. The document should contain pictures covering the various stages and subtypes of cancer.
- Data preprocessing: Preprocess the images to ensure that they are properly formatted and normalized. This may involve resizing the images, converting them to grayscale, and applying various image enhancement techniques.
- Model architecture: Design a deep convolutional network architecture that is appropriate for the task of cancer type identification. The architecture should consist of multiple layers of convolutional, pooling, and activation functions. Additionally, it should incorporate

techniques such as dropout, batch normalization, and data augmentation to prevent overfitting.

- Training: View the network using previous data. This includes tuning the hyperparameters of the network, such as the learning rate and the number of periods, and optimizing the loss using techniques such as stochastic gradient descent.
- Evaluation:Evaluate the performance of the training network on the test. This includes calculating various metrics such as accuracy, precision, recall and F1 score.
- Fine-tuning:Fine-tune the network to improve performance by adjusting hyperparameters and/or modifying the model. This will include the use of transfer learning, where the network is trained and optimized to identify different types of cancer before being used as a starting point.

Overall, building a deep convolutional network for cancer type identification requires expertise in both deep learning and medical imaging. It is important to work closely with medical professionals and domain experts to ensure that the network is appropriately designed and evaluated.Artificial neural networks are used in deep learning, a branch of machine learning, to model and resolve complicated issues. Deep learning algorithms are created to learn from a lot of data and are modeled after the structure and operation of the human brain.

Deep learning algorithms usually have many layers of neurons (also called nodes) interconnected in a hierarchical structure. Each layer learns to extract and represent differences from the input data, and the last layer produces the output model.

Deep learning's ability to learn hierarchical representation of data, which enables it to recognize complex patterns and relationships in data, is one of its main strengths. Therefore, deep learning is particularly useful for tasks such as games, speech recognition, image recognition, and natural language processing.

In this model, the dermoscopic data set is divided into two parts, training and testing. These forms are benign and malignant. Determine the cancer type by training the model using the Deep Network Designer tool.

1.1 Motivation for work

A set of disorders characterized by the body's unchecked proliferation and spread of aberrant cells are collectively referred to as cancers. It can affect practically any portion of the body and is a primary cause of death worldwide.

Cancer cells are cells that have undergone genetic mutations that allow them to reproduce and develop quickly without being constrained by the regular regulatory systems that control normal cells. These cells have the capacity to grow into tumors, encroach on surrounding tissues, and circulate throughout the body via the circulation or lymphatic system.

There are many different varieties of cancer, and each has special traits and available therapies. Breast cancer, lung cancer, prostate cancer, colorectal cancer, and skin cancer are a few frequent kinds of cancer.

Genetic abnormalities, contact with specific chemicals or substances, and lifestyle choices like smoking, eating poorly, and not exercising are only a few of the causes of cancer. Surgery, radiation therapy, chemotherapy, immunotherapy, and targeted therapy are all available as cancer treatments.

Successful cancer treatment and recovery depend on early detection. Mammograms, colonoscopies, and skin checks, among other routine cancer screenings, can aid in the early detection of cancer when it is still the most curable.

This project is focused on developing a system that can identify cancer in patients and categorize the type of cancer using Deep Convolutional Neural Network Algorithm.

1.2 Future Scope

Our goal is to create a method for identifying and categorizing different types of cancer. Specialists can use the system. This method will likely increase the sensitivity, specificity, and effectiveness of cancer screening since it uses image processing, pattern analysis, and computer vision techniques.Medical imaging projects main objective is to accurately and meaningfully extract information from these images with the least amount of inaccuracy. The development of auxiliary tools that can assist with early diagnosis or the monitoring of the cancer type identification and locations is made possible by the right combination and parameterization of the stages.To increase the storage such that any cancer can be detected using a single model so that a single model can identify various types of cancers in a person more accurately.

1.3 Objective

The objective for cancer type identification is to accurately determine the specific type of cancer a patient has based on the analysis of various biological samples, such as tissue or blood. This is important because different types of cancer require different treatment approaches, and accurate identification can help guide treatment decisions and improve patient outcomes. Additionally, identifying the specific type of cancer can aid in predicting the patient's prognosis and potential for recurrence. In order to achieve this objective, various techniques such as imaging, genetic testing, and molecular profiling may be used to analyze the patient's cancer cells and tissues.Algorithms based on machine learning and artificial intelligence can also be used to help identify the type of cancer, improving efficiency and accuracy.

1.4 Relevance

In our base paper, lung cancer has been identified using this DenseNet where CT images have been taken for training and Adaboost Algorithm is used for testing. Here, we used these dermoscopy photos for training and testing, and the accuracy of the validation was quite good.
The datasets used are the public datasets where any specialist can access for the training purpose. The predicted result obtained is using the testing.

CHAPTER 2

LITERATURE SURVEY

2. LITERATURE SURVEY

The durability and accuracy of predictive algorithms are especially important in diagnosis because results are important to patient care. Various popular distributions and integrations are used for forecasting. The purpose of classifying medical images is to identify their types and facilitate identification. Several classification and classification algorithms aim to improve the ability of diagnostic methods to predict anomalies.

We give a brief overview of the many approaches that have been suggested for cancer detection from 2002 to 2018 in the literature review.We have read a few publications, each of which contains information on a specific malignancy.The following information is supplied for each paper's summary.

2.1 D. Sharma and G. Jindal, "computer aided diagnosis for detection of lung cancer in CT scan images ," Int J. Comput. Elect. Eng., Vol.3, no. 5,pp. 714-718,Sep. 2011.

The article "Computer Assisted Diagnosis for Lung Cancer Detection on CT Scan Images" presents methods for diagnosing lung cancer on CT scan images. The plan includes image processing and machine learning algorithms to analyze CT images and identify areas suggestive of cancer.

The authors used data on CT images from cancer patients and healthy individuals. First, they preprocessed the CT image to enhance the lung area and eliminate noise. They then used a feature extraction technique to extract relevant features from the image. These features are used to train a support vector machine (SVM) to distinguish between healthy and cancerous regions of the lung.

The test results showed that it could detect cancer on CT scan images with 92.3 percent sensitivity and 91.2 percent specificity. The proposed system has the potential to help radiologists detect cancer at an early stage, thereby improving treatment quality and patient outcomes.

2.2 G. Huang, Z. Liu, and D. M. L. Van, ‘‘Densely connected convolutional networks,’’ in Proc. IEEE Conf. Computer. Vis. Pattern Recognit., Jul. 2017,pp. 4700–4708

The article introduces a new convolutional neural network architecture called Densely Connected Convolutional Networks (DenseNets). This article addresses the problem of depth loss in CNNs and improving information flow between layers.

The DenseNet architecture proposed in this study consists of several interconnected blocks. Each block has several convolutional layers, followed by a join operation that connects the input of the block to the outputs of all previous convolutional layers. This allows information to flow directly between layers, making it less likely that gradients will be lost. In addition, the authors introduce layers in the body in each block, reducing the number of ideas that illustrate the evolution of mathematics. The final output of the network consists of a global average pooling layer and a softmax layer.

The results show that DenseNets achieves good state-of-the-art performance across all datasets with fewer parameters than other CNN architectures. Additionally, the authors suggest that DenseNets are more efficient and easier to train than traditional deep CNNs because they require less time to assemble and there is less competition.

2.3 A. Krizhevsky, I. Sutskever, and G. E. Hinton, ‘‘Imagenet classification with deep convolutional neural networks,’’ in Proc. Adv. Neural Inf. Process. Syst., 2012, pp. 1097–1105

The authors introduce a deep neural network architecture called AlexNet and evaluate its performance on the ImageNet dataset. The AlexNet architecture consists of eight layers, including five convolutional layers and three fully connected layers. The authors use the corrected linear unit (ReLU) as the activation function and normal output to avoid overfitting. The mesh is trained using stochastic gradient descent (SGD) with strength and weight.

The results show that the proposed AlexNet architecture outperforms the previous state-of-the-art method, achieving a peak error rate of 15.3%, 10% higher than the past best method.

The authors also performed an ablation study to analyze the effects of different network components and found that the use of ReLU increased power, sustained release and significant amplification data to achieve the best performance.

2.4 Andre Esteva, Brett Krupel and Thrun Sebastian, "Deep Networks for Early Stage Skin Disease and Skin Cancer Classification", 2015.

The aim of the study by Andre Esteva, Brett Krupel, and Thrun Sebastian, titled "Deep Networks for Early Stage Skin Disease and Skin Cancer Classification," was to develop a deep learning algorithm capable of accurately classifying skin diseases and cancers at an early stage.

The authors train the algorithm using a deep convolutional neural network (CNN) architecture called Inception-v3. The database contains more than 129,000 medical images of skin diseases and cancers, including benign and malignant melanoma, seborrheic keratosis, and basal cell carcinoma, among others.

The findings showed that the deep learning system was very accurate in classifying skin diseases and cancer, some of which surpassed the performance of dermatologists. The algorithm ranks 91 percent for malignant melanoma classification, compared with 86.5 percent for dermatologists. The algorithm has also been more accurate when classifying other skin diseases and tumors, including brain tumors, squamous cell carcinoma, and seborrheic keratosis.

2.5 Brinker T, Hekler A, Utikal J, Grabe N, Schadendorf D, KlodeBerking C, Steeb T, Enk A, von Kalle C "Skin Cancer Classification Using Convolutional Neural Networks" : Med Internet Res 2018

This study named "Skin Cancer Classification Using Convolutional Neural Networks" was done by Brinker et al. and was published in the Journal of Medical Internet Research in 2018. The researchers aimed to examine the accuracy of convolutional neural networks (CNNs) in classifying skin cancer cells.

A dermatologist's first step in diagnosing malignancy is an examination of the skin area. Accurate diagnosis is important because of the similarities between some types of diseases; In addition, the accuracy of the diagnosis depends on the knowledge of the doctor. Dermatologists are 65%-80% accurate in diagnosing melanoma without additional support.

CNNs can be used to classify skin lesions in two different ways. On the other hand, CNNs were introduced before they became available for feature extraction from other big data sources such as ImageNet [18].In this case, the classification is done by other classifiers such as k-nearest neighbors, support vector machines, or neural networks. On the other hand, CNN can directly learn the relationship between raw pixel data and class labels through end-to-end learning.

Unlike traditional processes often used in machine learning, feature extraction is an integral part of the classification process rather than a separate, stand-alone step. If CNNs are trained using end-to-end, further research splits into two paths: learn the model from scratch or transfer the learning. But using a special training technique called transfer learning, millions of powerful CNN models cannot be used for classification even with a small amount of training data.

In this case, CNN was first trained using big data sources such as ImageNet; This is used as the first function of CNN. In particular, the final connection method of the CNN model is modified according to the number of training classes in real projects. There are two ways to train the CNN weights first: optimize all layers of the CNN, or freeze some layers due to overfitting and fine-tune only some layers outside of the grid.

2.6 Takiddin A, Schneider J, Yang Y, Abd-Alrazaq A, Househ M " Artificial Intelligence for Skin Cancer Detection": Scoping Review J Med Internet Res 2021;23(11):e22934

The aim of this study is to identify the types of AI algorithms used in skin cancer diagnosis, the types of skin cancer, the performance of the algorithms, and the limitations and difficulties associated with the use of AI in cancer diagnosis.

The authors searched several databases, including PubMed, Scopus, and Web of Science, and identified 49 studies that met the inclusion criteria. They analyzed these studies to identify the types of AI algorithms used, the type of skin cancer, the performance of the algorithms, and the limitations and challenges of using AI in diagnosis. The authors found that deep learning, particularly convolutional neural networks (CNNs), is the most widely used AI technique for cancer diagnosis. Clinical studies also show that AI algorithms have the potential to improve the accuracy and effectiveness of skin cancer diagnosis, especially when combined with clinical trials evaluated by a dentist. However, the authors note several limitations and challenges with the use of AI in skin cancer diagnosis, including the need for large datasets, diversity, potential bias in reporting, and issues with clinical practice and management.

The evaluation showed that AI has the potential to improve skin cancer diagnosis, but more research is needed to address the limitations and issues with its use. The review also highlights the need for collaboration between researchers, clinicians and policy makers to enable the safe and effective use of AI in healthcare. Overall, this article provides a comprehensive review of the application of AI in skin cancer diagnosis and recommends future research and treatments in this area.

2.7 JRay A, Gupta A, Al A Skin Lesion Classification With Deep Convolutional Neural Network: Process Development and Validation JMIR Dermatol 2020;3(1):e18438

91% are squamous cell carcinoma and only 8.33% are malignant melanoma. Most of the patients were from rural areas (88%) and many (92%) were working in agriculture."Artificial intelligence for cancer diagnosis" is a review published in the Journal of Medical Internet Research in 2021. This review aims to explore the current research situation regarding the use of artificial intelligence (AI) in cancer diagnosis.

The authors searched multiple electronic databases and identified 41 studies that met the inclusion criteria. The studies included in the review included various AI models, including convolutional neural networks (CNNs), support vector machines (SVMs), and decision trees. The results of reviews show that most studies have focused on classifying skin lesions as benign and malignant. These studies also report an accuracy of 86-99%, and the most commonly used models are CNN and SVM. The review also highlights several challenges with using AI to diagnose skin cancer, including a lack of standardization in obtaining reported images and annotations, limited quality data, and the need for further validation and clinical trials..

2.8 Rezk E, Eltorki M, El-Dakhakhni W Improving Skin Color Diversity in Cancer Detection: Deep Learning Approach 2022

The study titled "Improving Skin Color Diversity in Cancer Detection: Deep Learning Approach" was conducted by Rezk et al. and published in 2022. The authors aimed to improve the accuracy of skin cancer detection by addressing the issue of skin color diversity, which is often overlooked in existing studies.

The authors used a dataset of dermoscopic images of skin lesions that were collected from a dermatology clinic in Egypt. The dataset included images of skin lesions from individuals with different skin colors, including dark and light skin tones. The images were labeled as either benign or malignant based on their clinical diagnosis.

The authors used a deep learning model that included multiple convolutional layers and a fully connected layer. They used transfer learning techniques to fine-tune the model on their dataset, which allowed the model to learn features specific to skin lesions in the dataset.

The results of the study showed that the deep learning model achieved an accuracy of 87.3% in classifying skin lesions as benign or malignant. The model also demonstrated improved performance in detecting skin lesions in individuals with dark skin tones, which is an important step towards addressing the issue of skin color diversity in skin cancer detection.

The study suggests that deep learning models can be effective in improving the accuracy of skin cancer detection, particularly in addressing the issue of skin color diversity. The authors also highlight the importance of using diverse datasets in training deep learning models to ensure their generalizability to different populations.

2.9 N. Jalaboi R, Orbes Arteaga M, Richter Jørgensen D, Manole I, Bozdog O, Chiriac A, Winther O, Galimzianova A Explainability of Convolutional Neural Networks for Dermatological Diagnosis

The study titled "Explainability of Convolutional Neural Networks for Dermatological Diagnosis" was conducted by Jalaboi et al. and published in 2021. The authors aimed to investigate the explainability of convolutional neural networks (CNNs) in dermatological diagnosis, which refers to the ability to understand how the CNN arrived at its decision.

The authors used a dataset of dermoscopic images of skin lesions that were collected from a dermatology clinic in Romania. The dataset included images of skin lesions that were labeled as either benign or malignant based on their clinical diagnosis.

The authors trained a CNN model on the dataset and used a gradient-based approach to generate heat maps that highlighted the regions of the image that were most relevant to the CNN's decision. The authors also used a technique called saliency maps to identify the pixels in the image that had the most influence on CNN's decision.

The results of the study showed that the heat maps and saliency maps generated by the CNN model provided insight into the features of the skin lesions that the model was using to make its decision. The authors also found that the heat maps and saliency maps were able to highlight subtle differences in the features of benign and malignant skin lesions that were not easily detectable by human observers.

2.10 Skin lesion/ Cancer detection using deep learning Neema M, Arya S Nair, Annette Joy, Amal Pradeep Menon, Asiya Haris

Skin lesion/cancer detection using deep learning is an active area of research that has shown promising results in recent years. Deep learning models have been developed to assist dermatologists in diagnosing skin lesions by analyzing images of the lesions. These models have the potential to improve diagnostic accuracy and reduce the need for unnecessary biopsies.

One popular approach to skin lesion/cancer detection using deep learning is to train convolutional neural networks (CNNs) on large datasets of skin lesion images. The CNNs learn to identify the features that are most indicative of different types of skin lesions, such as asymmetry, border irregularity, color variation, and diameter. The trained model can then be used to classify new skin lesion images as either benign or malignant.

The researchers used a convolutional neural network (CNN) to train their model on the ISIC dataset. The CNN is a type of deep learning algorithm that is commonly used in image recognition tasks. The model was trained to classify skin lesions into different categories, including melanoma, basal cell carcinoma, and benign lesions.

The results of the study showed that the deep learning model was able to achieve high accuracy in classifying skin lesions. The model achieved an accuracy of 91.24% in detecting malignant melanoma, which is a highly aggressive form of skin cancer. The model also achieved high accuracy in detecting basal cell carcinoma and benign lesions.

CHAPTER 3

METHODOLOGY

3. METHODOLOGY

3.1 Data Preprocessing and Augmentation

These two are the crucial steps in preparing data for machine learning models. Data pre-processing is important because it helps to clean and transform data into a format that is more easily understood by machine learning algorithms. Raw data often contains inconsistencies, missing values, and errors that can negatively impact the accuracy of the models trained on that data. By pre-processing data, we can remove such inconsistencies and errors, and ensure that the data is in a format that can be used effectively by machine learning models.

Data augmentation is important because it increases the size of the data set, which in turn improves the performance of machine learning models. In many cases, the amount of available data is limited, and this can result in overfitting and poor generalization of machine learning models. By augmenting the data, we can generate new data samples that are similar to the original data, but with some variation. This helps to improve the performance of machine learning models and reduce overfitting. There are several methods for data pre-processing and augmentation.

Data Cleaning involves identification and handling missing data, removing duplicates, and handling outliers if necessary. Data Integration involves combining data from multiple sources if required. Data Transformation is for normalizing or standardizing the data to bring it into a common range, scaling the data, encoding categorical variables, and converting data into numerical format. Data Augmentation for generating new data samples by applying various techniques such as rotating, flipping, cropping, and adding noise to the existing data.

Data pre-processing typically involves several steps, including:

1. Data cleaning: removing missing or invalid data points, outliers, and duplicates.
2. Data normalization: scaling the data to a common range, such as between 0 and 1, or standardizing the data to have a mean of 0 and a standard deviation of 1.
3. Data transformation: converting categorical data into numerical form, or reducing the dimensionality of the data using techniques such as principal component analysis (PCA) or t-distributed stochastic neighbor embedding (t-SNE).

Data augmentation involves generating new data from existing data by applying transformations, such as:

- Image augmentation: rotating, flipping, cropping, or scaling images.
- Text augmentation: replacing words with synonyms, inserting or deleting words, or shuffling sentences.
- Audio augmentation: changing the pitch, speed, or volume of audio recordings.

3.2 DenseNet

DenseNet (Dense Convolutional Network) is a deep learning architecture that is a modification of the traditional convolutional neural network (CNN) architecture, which introduces a novel connectivity pattern between layers. DenseNet — In comparison to ResNet and Pre-Activation ResNet, Dense Convolutional Network (Image Classification) achieves great accuracy with few parameters and dense connections. So let's check how it functions.

3.2.1 Dense Block

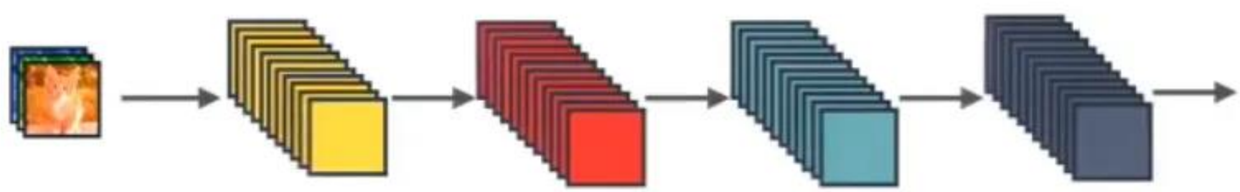

Figure 1: Standard ConvNet Concept

In the ConvNet model, an input image is processed through multiple convolutional layers, with each layer extracting higher-level features from the input. The output of one convolutional layer becomes the input of the next, allowing the network to learn more features. Based on the inputs of all convolutional processes, the input is transformed into a series of high-level maps that capture the most important parts of the image. These feature maps can be used for tasks such as image classification, object detection, and segmentation.

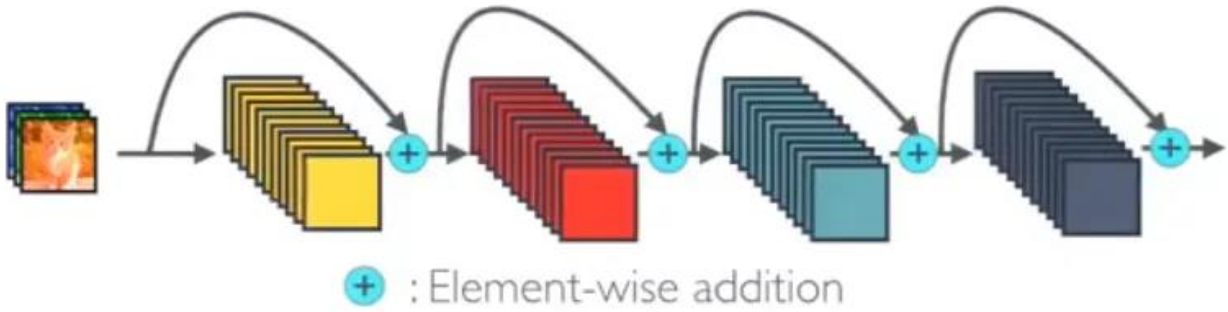

Figure 2 :ResNet Concept

In ResNet (short for Residual Network), the identity mapping is used to promote the propagation of gradients during training. The residual blocks in a ResNet use an identity shortcut connection that allows the gradient to flow more easily through the network. The identity shortcut connection simply adds the input of a residual block to its output, bypassing one or more convolutional layers. This operation is performed using element-wise addition.

The identity shortcut connection in ResNet can be viewed as a state that is passed from one ResNet module to another. By preserving the gradient flow and passing the input signal unchanged, the residual blocks in ResNet can learn to model the residual mapping, i.e., the difference between the input and output of the block. This approach allows ResNet to be trained deeper than traditional convolutional neural networks, with fewer vanishing gradients.

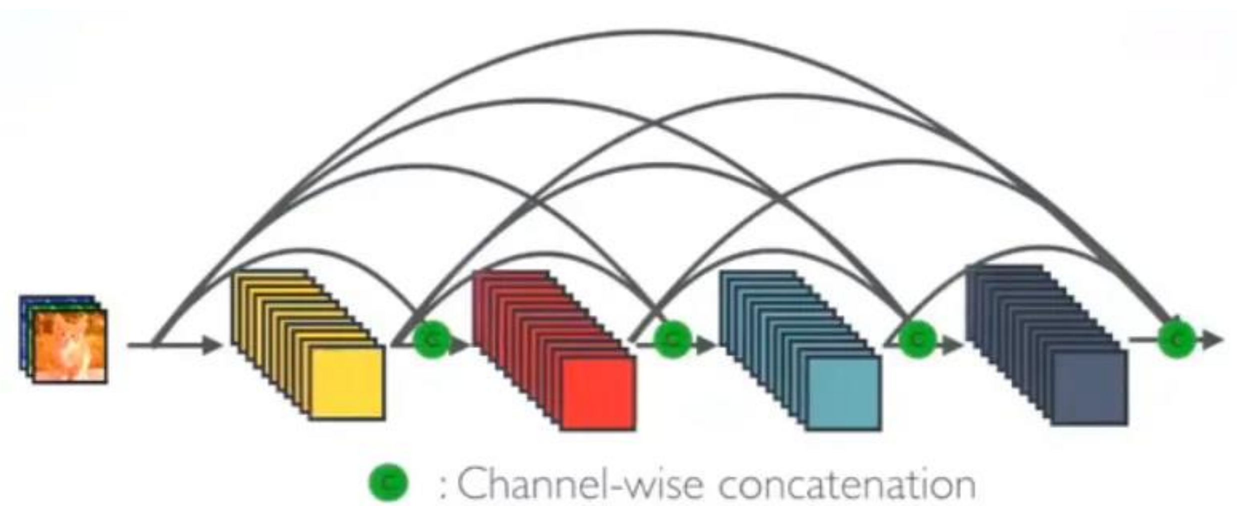

Figure 3 : One Dense Block in DenseNet

In DenseNet, each layer receives additional inputs from all preceding layers in the network and passes on its own feature maps to all subsequent layers. The outputs of all previous layers are concatenated together and used as input to the current layer. This is known as a dense connectivity pattern, which allows each layer to receive a "collective knowledge" from all preceding layers.
By densely connecting each layer to all preceding layers, DenseNet can make more efficient use of the available parameters, improving both training speed and accuracy. The dense connectivity pattern also promotes feature reuse and allows the network to be deeper without suffering from vanishing gradients.

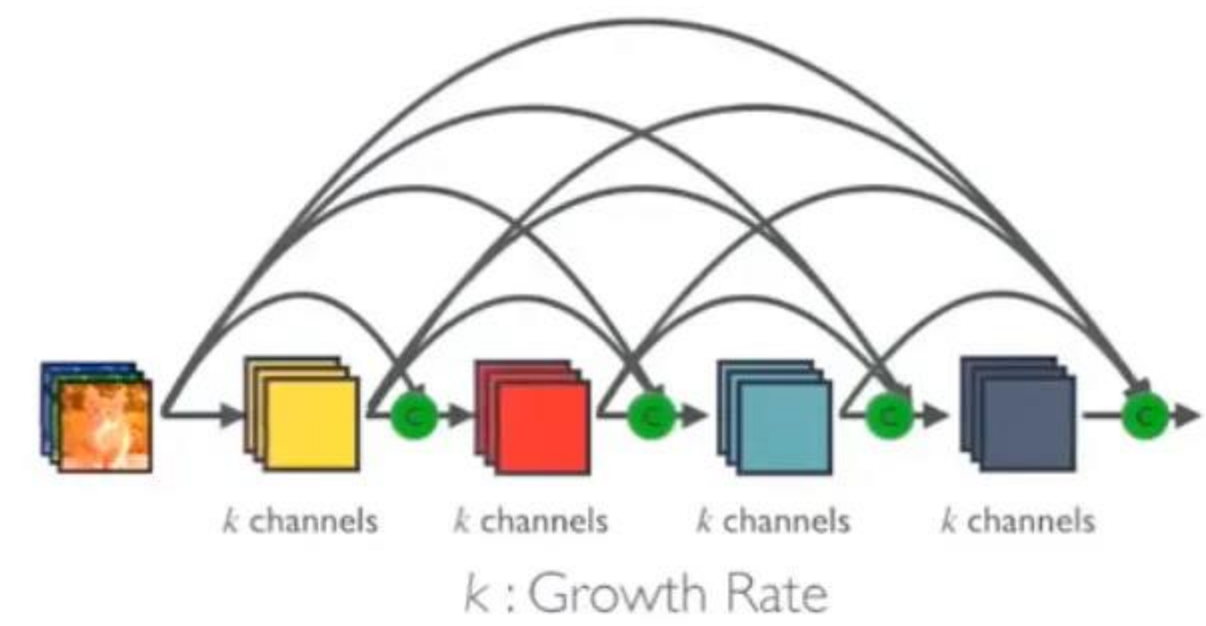

Figure 4 : Dense Block in DenseNet with Growth Rate k

The growth rate k in DenseNet determines the number of additional channels that are produced by each layer in the dense block. By increasing the growth rate, the network can learn more diverse and complex features,while decreasing the growth rate can reduce the number of parameters and improve the computational efficiency of the network. The following figure shows the concept of concatenation during forward propagation:

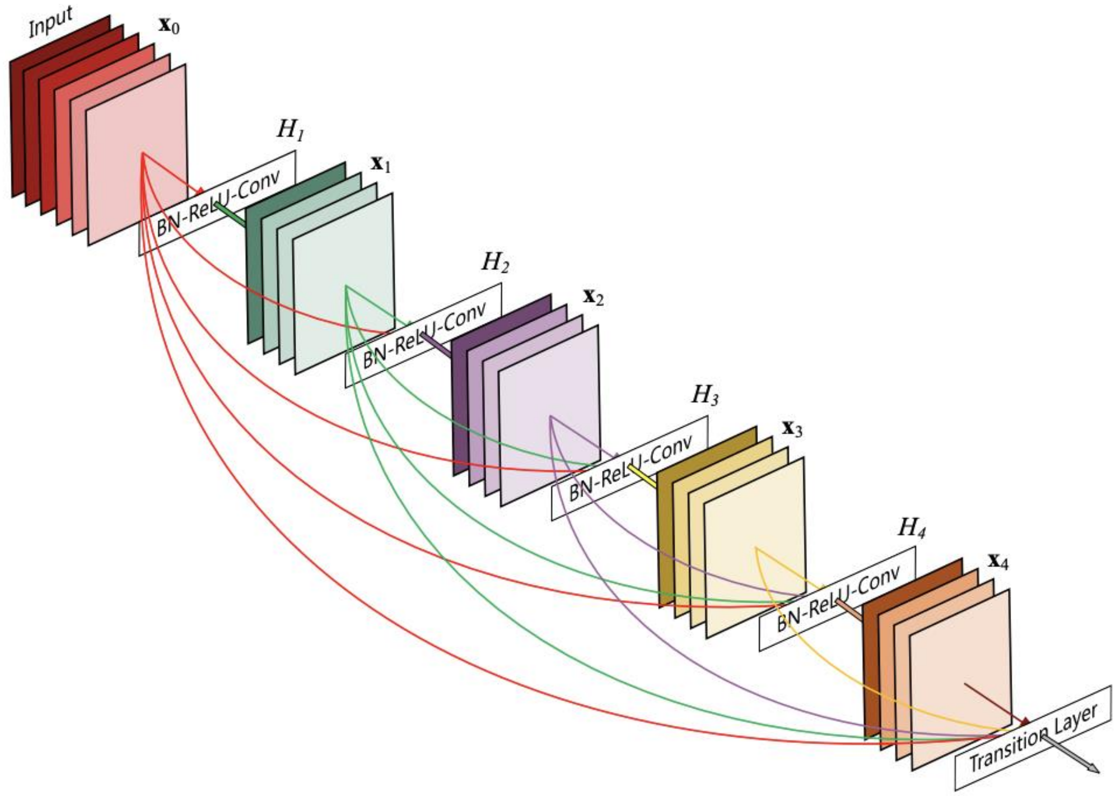

Figure 5 : 5 layers Dense Blocks with growth rate of k=4

A Dense Block is a module in convolutional neural networks where each layer is directly connected to every other layer within the block. The connections between the layers are created by concatenating the feature maps of each layer with the feature maps of all previous layers, allowing the network to access a wide range of features at each layer.

This method of concatenating the feature maps is different from the ResNet architecture, where the feature maps are added together before being passed on to the next layer. By concatenating the feature maps in a Dense Block, the network can access a more diverse range of information, which can help to improve the accuracy of the model. Additionally, the use of dense connections helps to reduce the number of parameters in the model, making it more efficient and easier to train.

3.2.2 DenseNet-201 Architecture

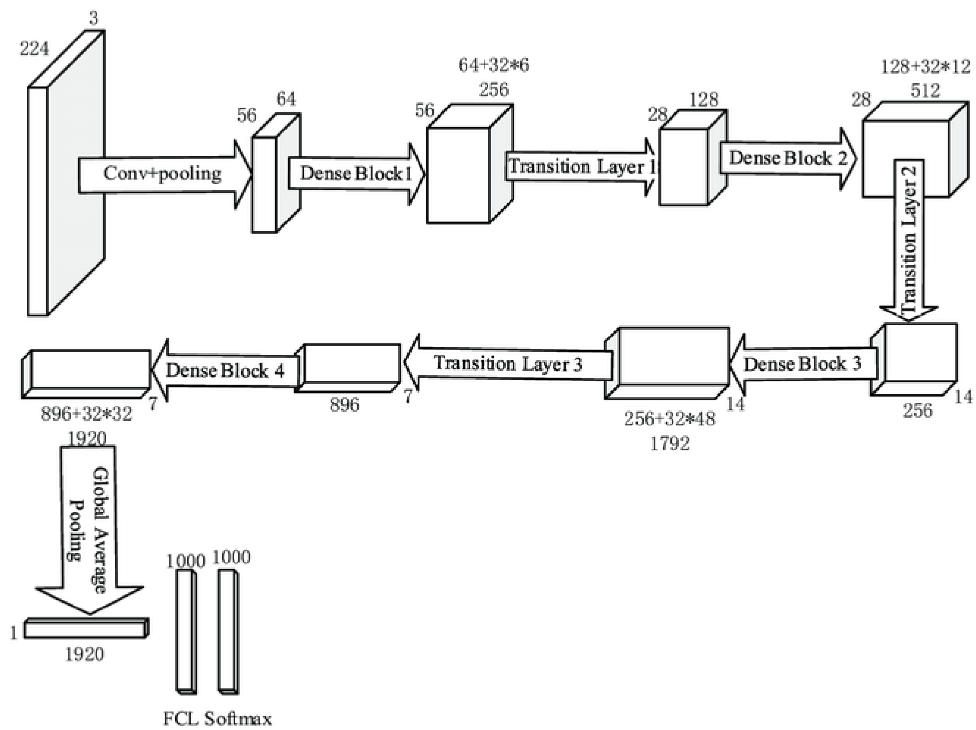

Figure 6: Densnet-201 architecture

DenseNet-201 is a deep convolutional neural network architecture that was developed by Huang et al. in 2017. It is a variant of the DenseNet architecture, which is known for its dense connectivity pattern between layers. DenseNet-201 has 201 layers and is widely used for various computer vision tasks, including image classification, object detection, and segmentation.

The DenseNet-201 architecture consists of four dense blocks, each of which contains a set of densely connected convolutional layers. Each dense block takes as input the feature maps from the previous block and passes its own feature maps as input to the next block. This dense connectivity pattern allows for better gradient flow and feature reuse, which can improve the network's performance.

Between the dense blocks, there are transition layers that perform downsampling and reduce the number of feature maps to avoid overfitting. The transition layers consist of a batch normalization layer, followed by a 1x1 convolutional layer and a 2x2 average pooling layer.

At the end of the last dense block, there is a global average pooling layer that averages the feature maps over the spatial dimensions, followed by a fully connected layer and a softmax activation function that produces the final output.

DenseNet-201 has several advantages over other deep learning architectures. Its dense connectivity pattern reduces the number of parameters, making the network more computationally efficient. It also has lower memory requirements and can be trained with smaller batch sizes. Additionally, DenseNet-201 has achieved state-of-the-art performance on several benchmark datasets, including ImageNet, which contains over a million images.

DenseNet-II design is based on some deep learning algorithms such as DenseNet (Sun et al., 2020), VGG-16 (Mateen et al., 2019), InceptionV3 (Albatayneh et al., 2020) and ResNet (Khan et al., 2020). al., 2019).
et al., 2020). 2019).

Extracts important features from each algorithm and combines them to create a powerful classification system. Any research that uses more than one model can be further divided into phases.These usually include data analysis, preliminary data, classification of data for training and testing, modeling and training data for this, and finally the evaluation of performance on our test data sample was good. The layers used to build the DenseNet-II model are summarized as follows:

I. Conv2d Layer: applies a filter to a 2D input image to produce a smaller output feature map by computing dot products between filter weights and pixel values, with learned weights through backpropagation.
II. Conv Maxpool 2d Layer: Use the Conv2D process followed by max pooling to reduce the size and de-features of the
III. Flatten Layer: This process compresses features and functions into columns to facilitate more efficient processing.
IV. Dense Layer: This is the simplest technique in which an activation function is applied to several connected neural networks to generate nonlinear output.

Dense network functionality is a combination of optimization and ReLU functionality. Normalization is done in batches by passing an input with zero mean and unit variance.

There was a short process while creating the design, now we can write the design as shown.

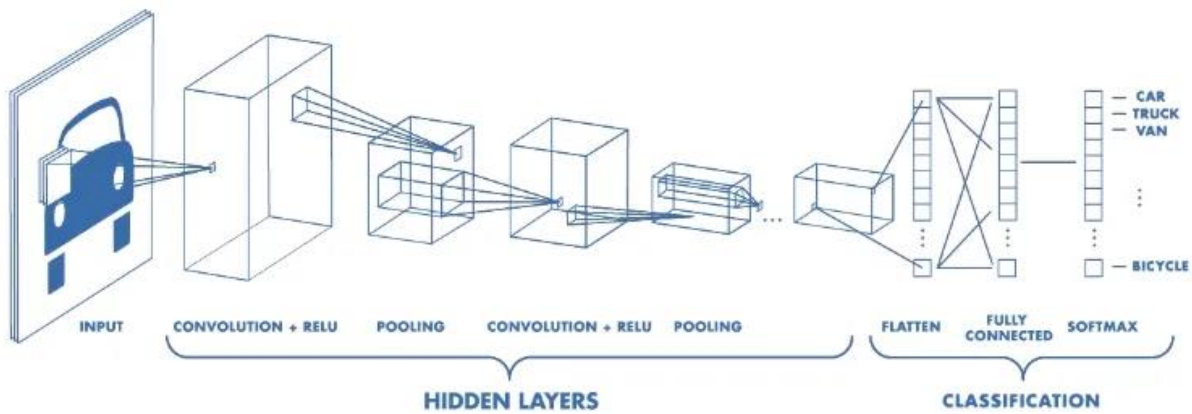

Figure 7: DenseNet architecture example

A CNN typically has three layers: a convolutional layer, a pooling layer, and a fully connected layer.

1. Convolution Layer

Convolutional techniques are a type of layering in a convolutional neural network (CNN), often used in image and signal processing. This layer contains multiple filters (also called kernels or weights) that combine the input data to create the output image. The basic idea behind the convolutional layer is to catch local patterns in the input data and learn the representation of the data. Each filter in this process scrolls through the input data, calculating the weight of the current filter and the local area of the input data. This function ensures that the value is obtained once at the corresponding point in the output map.

The size of the output feature map is determined by the size of the input data, the size of the filter, and the step size (step) that the filter moves over the input data. In general, convolutional layers rely on pooling layers that subsample the output feature map to reduce its size and improve performance. If we have input of size

W x W x D, number of cores D of length F, steps S and fill P, the output volume can be calculated by the following formula.

$$W_{out} = \frac{W - F + 2P}{S} + 1$$

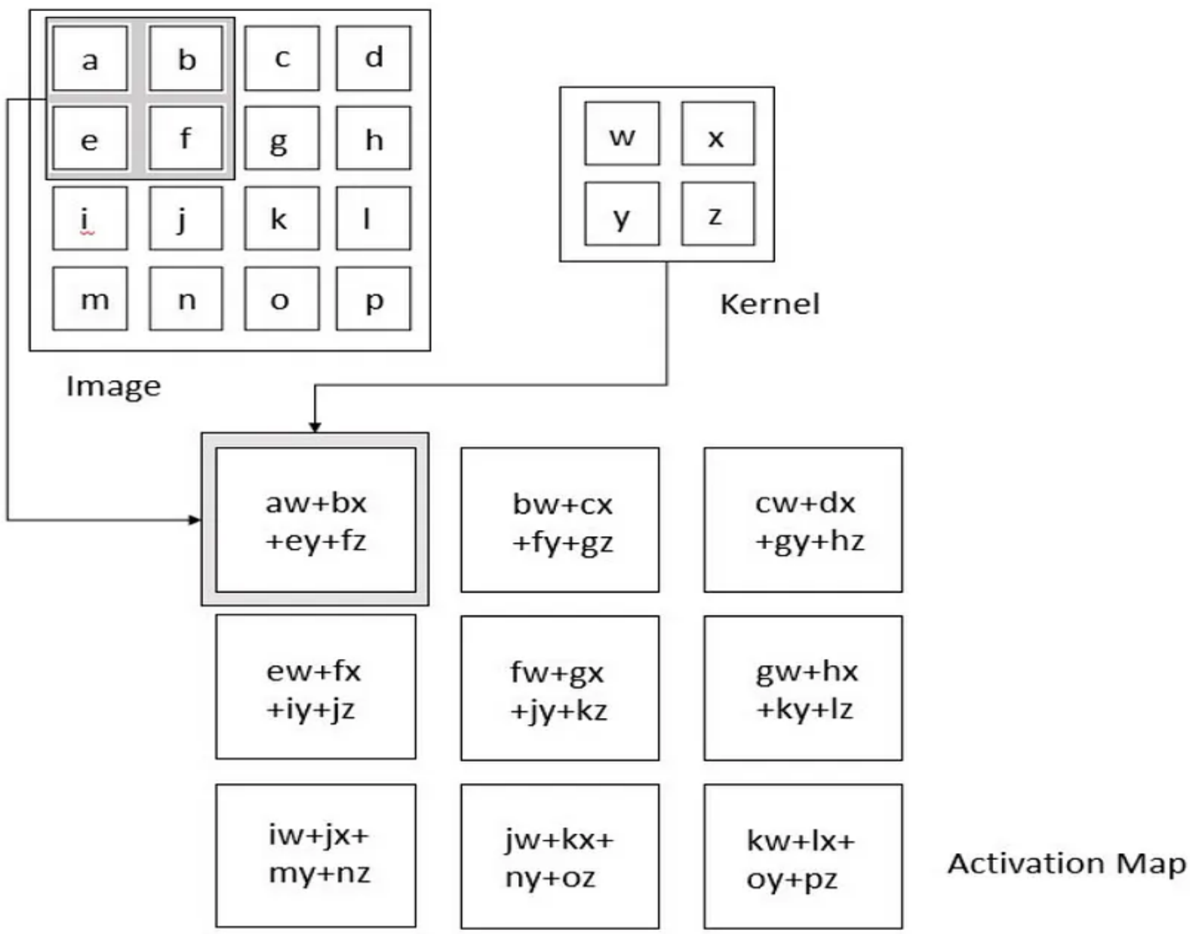

Figure 8: Convolution Operation (Source: Deep Learning by Ian Goodfellow, YoshuaBengio, and Aaron Courville)

2. Pooling Layer

The pooling layer operates on each feature map independently, and its main purpose is to downsample the input by aggregating local information. This can help to reduce the computational cost of subsequent layers, improve robustness to small shifts and distortions in the input, and increase the effective receptive field of the network.

There are different types of pooling layers, such as maximum pooling, average pooling, and L2 pooling. Maximum pooling is the most common type where the maximum value in each region of the map is selected and passed to the next layer. Average pooling works the same way, but uses the average instead of the maximum in each local area. L2 pooling uses the square root of the sum of the squares of the values in each local area.

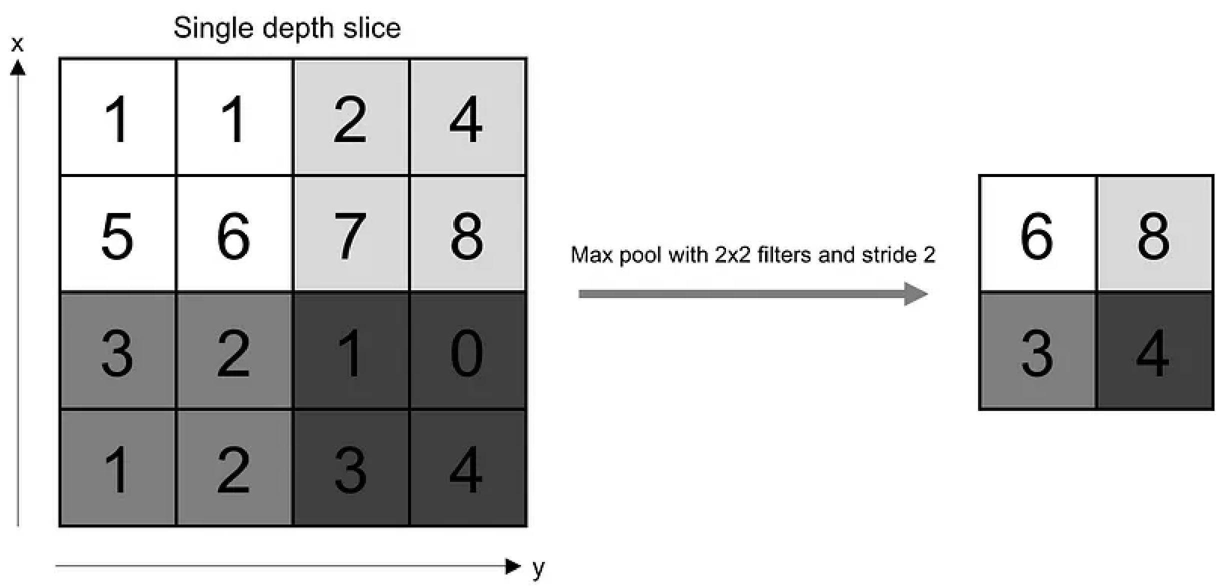

Figure 9: Pooling Operation (Source: O'Reilly Media)

If we have a map with dimensions W x W x D, dimensions F and step S, it can be calculated using the size of the output volume.

$$W_{out} = \frac{W - F}{S} + 1$$

This results in the output of the amount of Wout x Wout x D. With integration, an object can be defined at any time regardless of where it is in the frame because some definition language is not consistent.

3. Fully Connected Layer

Fully Connected Layer is a layer used in neural networks where all nodes (neurons) in one layer are connected to all nodes in the next layer. In other words, every neuron in the current layer is connected to every neuron in the next layer.

In a fully connected layer, every link has a weight and every neuron has a negative effect. During forward propagation of a neural network, the input data is weighted and then added to the error time of each neuron in the cluster. The result is passed through the activation function, which causes the neuron to exit. Layer is often used in deep learning models, especially the last layer of classification or networking. It allows the model to learn the unique relationship between material and material and can capture higher properties of the data.

4. Non-Linearity Layers

Nonlinearity layers are a type of layer commonly used in neural networks to introduce nonlinearities into the network. Nonlinearities are important because they allow neural networks to model complex functions that would otherwise be impossible to represent with linear models.

There are several types of nonlinearity layers commonly used in neural networks, including:

1.ReLU (Rectified Linear Unit) Layer

This layer applies the function f(x) = max(0,x) to the input. This effectively "turns off" any negative values in the input, which can help to prevent the vanishing gradient problem that can occur in deep neural networks.

2.Sigmoid Layer

This layer applies the sigmoid function f(x) = 1/(1+exp(-x)) to the input. The sigmoid function has a "S"-shaped curve and can be used to map any input value to a value between 0 and 1. Sigmoid layers were commonly used in the past, but are now less popular due to issues with vanishing gradients and saturation.

3.Tanh (Hyperbolic Tangent) Layer

This layer applies the hyperbolic tangent function f(x) = (exp(x)-exp(-x))/(exp(x)+exp(-x)) to the input. Like the sigmoid function, the tanh function has an "S"-shaped curve, but maps inputs to values between -1 and 1. Tanh layers are still used in some neural networks, particularly in recurrent neural networks.

4.Softmax Layer

This layer is commonly used in the output layer of a classification network. It takes a vector of input values and normalizes them so that they sum to 1.0. This can be thought of as a way to convert the input values into probabilities that can be used to classify the input into one of several classes.

3.2.3 Advantages of DenseNet

Improved accuracy: DenseNet-201 has shown improved accuracy over other CNN architectures on various image classification tasks, including the ImageNet dataset.

1. Parameter efficiency: DenseNet-201 uses fewer parameters than other CNN architectures with similar performance, making it more efficient and reducing the risk of overfitting.
2. Better feature reuse: DenseNet-201 allows for better feature reuse by connecting each layer to every other layer in a feed-forward fashion. This means that the output of each layer is concatenated with the output of all previous layers, providing a richer feature representation.
3. Reduced vanishing gradient problem: DenseNet-201 can reduce the vanishing gradient problem that can occur in deep neural networks because of the direct connections between the layers.

4. Flexibility: DenseNet-201 can be used for a wide range of tasks, including image classification, object detection, and segmentation.
5. Faster convergence: DenseNet-201 has been shown to converge faster than other CNN architectures, reducing the time and resources required for training.
6. Robustness: DenseNet-201 has been shown to be robust to noisy and incomplete data, making it suitable for real-world applications.

3.2.4 Disadvantages Of Densenet

DenseNet merges each map layer with the previous layer and repeats the data multiple times. DenseNet is a neural network architecture that has gained popularity in computer vision because it overcomes the gradient matting problem and improves the information flow in the network. However, like any other neural network architecture, DenseNet has some disadvantages such that training is computationally intensive and requires a lot of memory to store models.

1. Tendency to overfit: DenseNet can lead to overfitting, especially if the model is very complex or training data is limited.
2. Interpretation issues: DenseNet is a deep neural network architecture with many layers and it is difficult to explain the relationship between input and output.
3. Sensitivity to hyperparameters: To be effective, DenseNet needs to carefully tune hyperparameters such as learning rate, stack size, and regularity.
4. Usage limitations: DenseNet is primarily intended for tasks in the visual field such as image classification, segmentation, and object detection, but may not be suitable for other types of processing such as natural language processing or physical analysis.

CHAPTER 4

PROPOSED APPROACH

4. PROPOSED APPROACH

Below is an example of skin cancer classification using DenseNet:

- Data Collection: Data collection on skin cancer images, including different types of cancer and images of healthy skin.

- Data Preprocessing: Preprocessing by resizing images, normalizing pixel values, and augmenting datasets with techniques such as flipping, rotating, and scaling.

- Split Dataset: Split the dataset into training, validation, and test sets.

- Change Tutorial: Initialize the pre-trained DenseNet model and set it on the skin data. Cool down some layers of the mesh to avoid overloading.

- Training: Use training data to train the model and monitor the performance of the validation process. Use a lossy algorithm like categorical cross-entropy and an optimizer like Adam.

- Hyperparameter Tuning: Optimize hyperparameters such as learning rate, stack size and optimization.

- Evaluate: Evaluate the model's performance on test data using metrics such as accuracy, precision, recall, and F1 score.

- Description: Use visualization techniques such as Grad-CAM to understand where the image pattern is split.

- Deployment: Put the training model in a web app or mobile app for real-time cancer diagnosis.
- Overall, DenseNet can be an effective tool for skin cancer classification due to its ability to learn intricate features from medical images, and with proper preprocessing and

hyperparameter tuning, it can achieve high accuracy in predicting different types of skin cancer.

4.1 Datasets

Many cancer treatment materials are available for research and development. Here are some popular images:

1. ISIC (International Skin Imaging Collaboration) Archive: This is a collection of more than 33,000 dermoscopic and therapeutic images of the skin, including melanomas, moles, and other skin conditions. It is one of the largest and most diverse cancer treatment databases available.
2. HAM10000 (Man vs. Machine with 10,000 training images) dataset: This is a dataset containing more than 10,000 dermoscopic images of skin diseases, including seven types of skin cancer. It is curated by the Department of Dermatology at the Medical University of Vienna.
3. PH2 dataset: This is a dataset containing 200 dermoscopic images of benign and malignant pigmented skin. This information includes accurate ground segmentation masks and treatment information.
4. SKIN-100 dataset: This is a dataset of 100 skin images, including 50 severe lesions and 50 benign lesions. These data are designed for evaluation of skin detection algorithms.
5. Dermophyte Image Library: This is a database containing more than 1300 medical images of dermatology diseases, including melanoma and non-melanoma tumors.

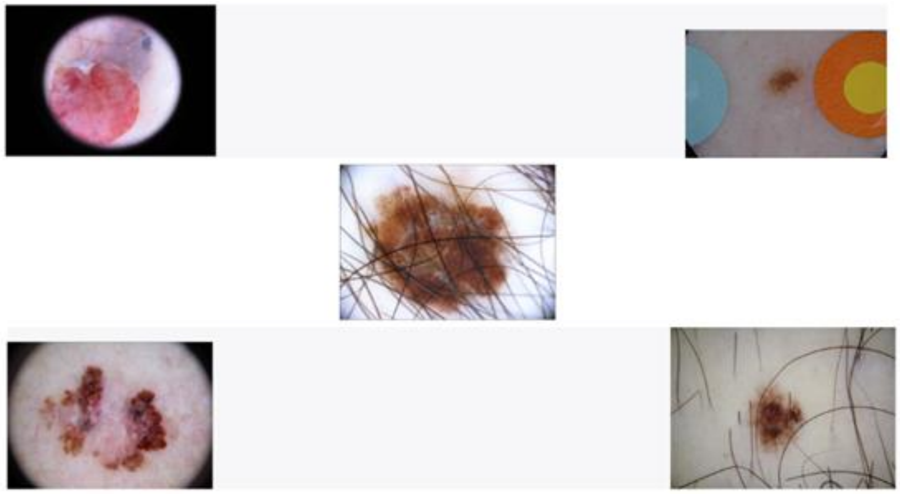

Figure 10: Dermoscopyimages(benign & malignant)

Dataset can be in many forms, including numbers, text, images, audio, video, or a combination of these. Datasets can be created in many ways, such as research, experiment, observation, or data collected from various source.

In the context of machine learning, data can be used to train and evaluate models. The data is usually divided into two or three parts: the training set, the validation set, and the test set. The training method is used to train the model, the validation method is used to tune the hyperparameters to avoid overfitting, and the test method is used to evaluate the model's performance on the data parameters.

A dataset is a collection of data created and presented in a specific format for analysis and interpretation. Information can be obtained from a variety of sources, including public archives, private organizations, and handbooks. The data here is taken from the public website Kaggle. Data from tumor samples were used for training and testing. The file is stored 3 kb and contains benign and malignant CT images.Of these, 50 benign images and 50 malignant images are used for training purposes.

4.2 Training Procedure

The predefined image classification grid can divide the image into 1000 objects, including keyboards, coffee mugs, pens and various animals. These networks learned more than a million images. The mesh creates a representation for many images. With an image-based input, the grid returns a label for each object in the image and values for each class.

Deep learning applications are often used in non-academic applications.Pre-trained networks can be used as a starting point for learning new features. Transfer learning is usually faster and easier than starting from scratch and using random sampling to set up the network. You can use the acquired skills immediately.

4.2.1 Training process flow chart

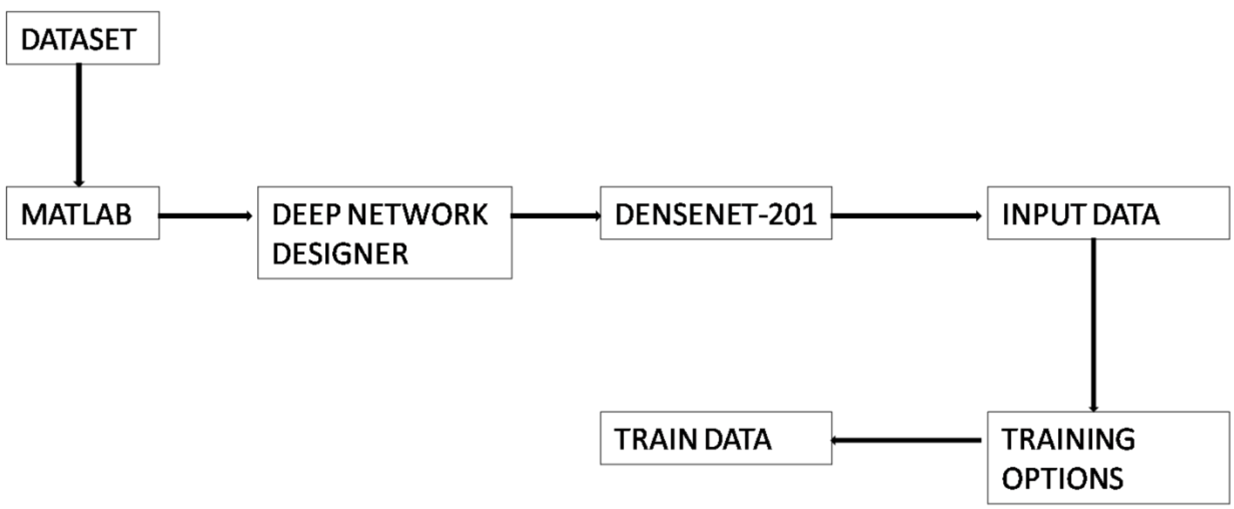

Figure 11:Training block diagram

Densenet-201 is a convolutional neural network architecture that is used for image classification. The training procedure for Densenet-201 typically involves the following steps:

I. Data preprocessing: The training data is preprocessed to ensure that it is of the correct format and is properly normalized. This may include resizing the images, applying data augmentation techniques such as random cropping and flipping, and normalizing the pixel values.

II. Initialization: The weights of the Densenet-201 network are randomly initialized using a normal distribution.

III. Forward Propagation: The input image is fed over the network and the results of each layer are calculated using the forward propagation method.

IV. Loss calculation: calculate the loss by comparing the network output with the actual ground map to measure the difference between the estimated output and the actual output.

V. Back propagation: Use the back propagation algorithm to calculate the gradient of the loss function with parameters.

VI. Optimization: Adjust the weight of the mesh using optimization methods such as Stochastic Gradient Descent (SGD) or Adam.

VII. Studies are updated periodically to adapt the model to the correct solution.

VIII. Validation: During training, the performance of the model is evaluated on the validation set to monitor for overfitting and ensure that the model generalizes well to new data.

IX. Hyperparameter Setting: Adjust the hyperparameters of the network such as learning rate, heap size, weight and find the best location for the network.

X. Iteration: Repeat the above steps several times until the model converges to complete the validation process. Finally, the training model can be used to make predictions on new, unseen data.

4.3 Testing Procedure

Testing in Digital Image Processing involves evaluating the performance of image processing algorithms on a set of test images. The goal is to determine how well the algorithm performs on different types of images and under different conditions. It is essential to test image processing algorithms on a variety of test images to ensure that they can generalize well to new data. This helps to ensure that the algorithm's output is accurate and reliable in real-world scenarios. Furthermore, it is essential to use evaluation metrics that are appropriate for the specific image processing task to ensure that the algorithm's performance is accurately assessed.

One of the advantages of DenseNet is that it can be trained with fewer parameters than other convolutional neural networks. This can lead to faster training times and better performance on smaller datasets. However, it is still important to test the DenseNet model on a separate dataset to ensure that it can generalize well to new data.

4.3.1 Testing process flowchart

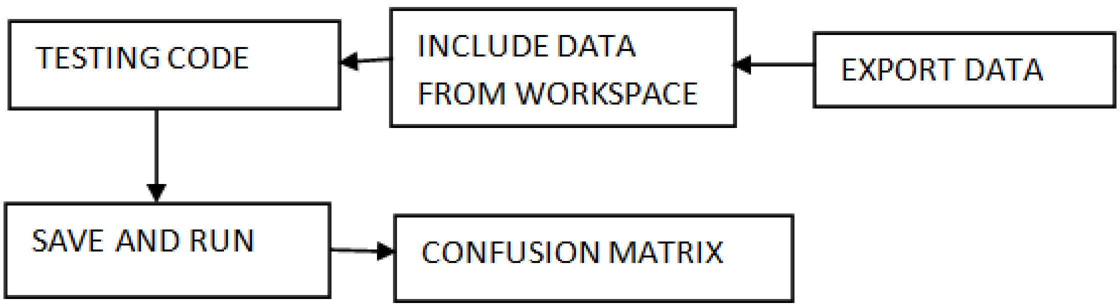

Figure 12: Testing block diagram

To perform testing in DenseNet, you can follow these steps:

- Load the saved model: Once you have trained the DenseNet model, you can save the weights of the model to disk. To perform testing, you need to load the saved model using a suitable deep learning framework such as TensorFlow, PyTorch, or Keras.

- Export the model to workspace: After loading the model modify the layers which already exist. i.e.,change the parameters of the Fully connected layer so that the classification exists in between the two outputs and add the classification layer by removing the existing layer of the model so that any number of images can be given.

- Load the test data: Load the test dataset, which is a set of skin images that the model has not seen before. Make sure the test dataset is in the same format as the training dataset and has the same preprocessing steps applied.

- Evaluate the model: Use the loaded model to make predictions on the test dataset and evaluate the model's performance using suitable evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics will help you understand how well the model generalizes to new, unseen data.

- Visualize the predictions: To get a better understanding of how the model is making predictions, you can visualize the predictions on a few samples from the test dataset. This will help you identify any patterns in the predictions and understand how the model is making decisions.

- Fine-tune the model: Based on the evaluation results, you can fine-tune the model by tweaking the hyperparameters such as learning rate, batch size, and number of layers. This can help you improve the model's performance on the test dataset.

- Repeat the process: Once you have fine-tuned the model, you can repeat the process of testing and evaluation to see if the changes have improved the model's performance.

- Overall, testing in DenseNet involves loading the saved model, loading the test dataset, making predictions, evaluating the model, visualizing the predictions, and fine-tuning the model if necessary. By following these steps, you can ensure that your model performs well on unseen data and is ready for deployment.

It's worth noting that skin cancer detection using deep learning models is an active area of research, and there are many challenges to be addressed, such as class imbalance, dataset bias, and interpretability. Therefore, it's important to carefully evaluate the model's performance and interpret the results before deploying it in a real-world setting**.**

CHAPTER 5

RESULTS

5.RESULTS

5.1 Training Results

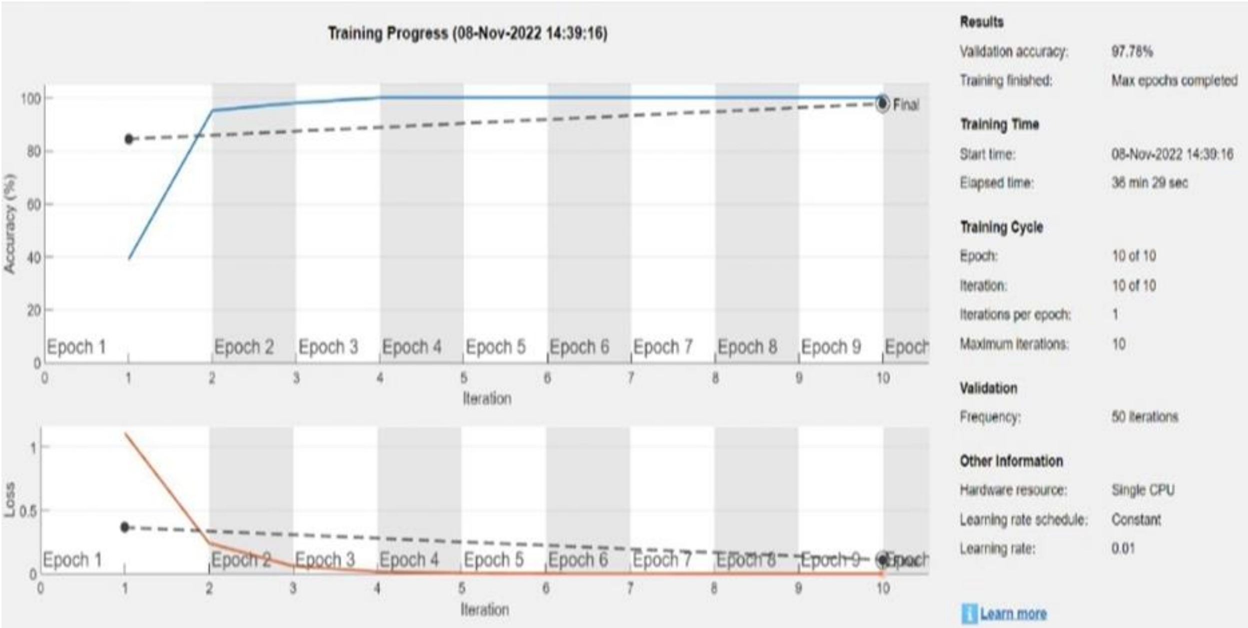

Figure 13:Training result 1

The above shown graph has 10 epochs (a particular period of time) with a validation accuracy of 97.78% . Here, a learning rate of value 0.01 has been given. When training a DenseNet-201 model on a new dataset, it is important to carefully tune the hyperparameters and use appropriate data augmentation techniques to prevent overfitting and improve generalization performance. Additionally, transfer learning with a pre-trained model can often accelerate the training process and improve overall accuracy.

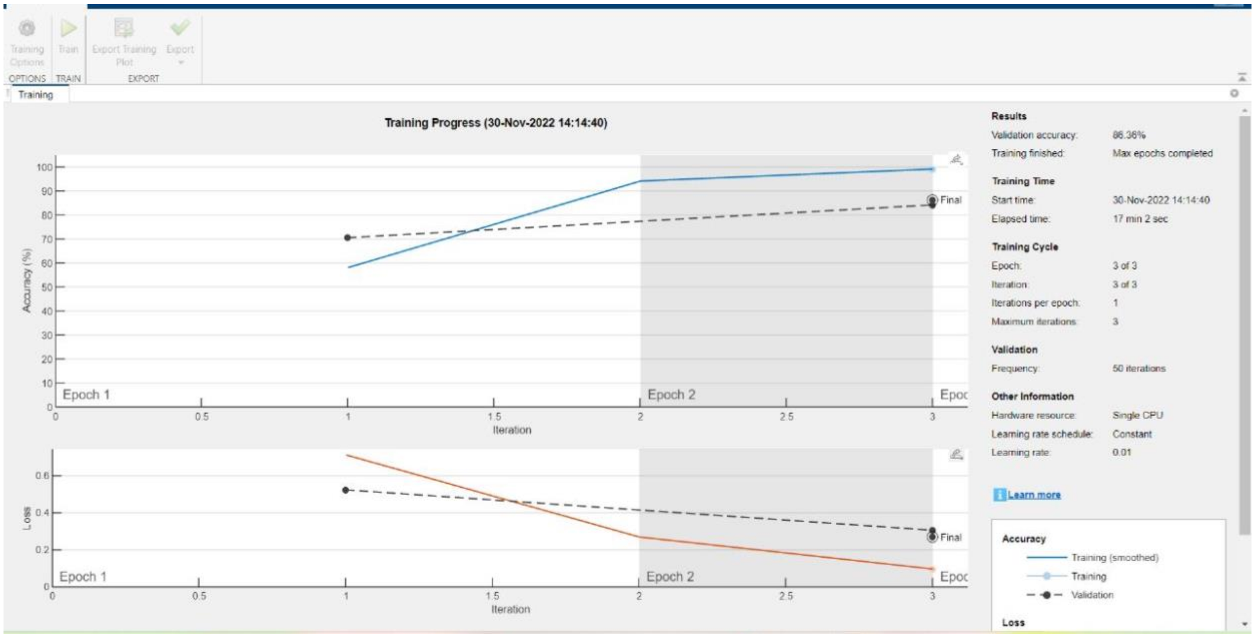

Figure 14: Training Result 2

5.2 Testing Results

Figure 15: Confusion matrix or prediction result

Confusion matrix:

The confusion matrix is a table often used to measure the performance of machine learning models. A confusion matrix shows the number of positive (TP), negative (TN), negative (FP), and negative (FN) for a classification problem. In this confusion matrix, the rows represent the predicted classes and the rows represent the actual classes. Each cell of the matrix represents the number of events belonging to a particular class.

True Positive (TP) - These are instances where the model correctly predicts the positive class.
True Negatives (TN) - These are instances where the model correctly predicts the negative class.
False Positives (FP) - These are instances where the model is incorrect for the positive class (Type I error).
False Negatives (FN) - These are instances where the model incorrectly predicts the negative class (type II error). The results in the confusion matrix show accuracy, accuracy, recall rate, F1 score, etc., which helps to evaluate performance well across all machine learning models. It can be used to calculate various performance metrics.

CHAPTER 6

CONCLUSION

6. CONCLUSION

6.1 Conclusion

Convolutional neural networks (CNNs) have demonstrated significant potential in recent years for the detection of skin cancer. CNNs can learn to recognise tiny patterns and traits that can be symptomatic of malignant growths or other abnormalities by training on massive datasets of medical pictures.

Several studies have shown that CNNs are effective at detecting skin cancer using a variety of imaging modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), and mammography. (MRI). In other instances, CNNs have even been able to spot malignant tumors better than human experts.CNNs have the potential to dramatically increase the accuracy and efficiency of skin cancer diagnosis and treatment, while there are still certain issues that need to be resolved, such as the requirement for more diverse and representative datasets. Going forward,

6.2 Future Scope

The proposed approach can be further improvised by::

- Increasing the storage for various datasets such that the training for different cancer datasets can be done by a single model.
- The training iteration time can also be reduced further.

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