Bachelor of Science in Computer Science & Engineering

Detection and Diagnosis of Breast Cancer using Convolutional Neural Network

by

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Submitted in partial fulfilment of the requirements for
Degree of Bachelor of Science
in Computer Science & Engineering

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The thesis titled '**Detection and Diagnosis of Breast Cancer using Convolutional Neural Network'** submitted by ID: 1504084, Session 2019-2020 has been accepted as satisfactory in fulfilment of the requirement for the degree of Bachelor of Science in Computer Science & Engineering to be awarded by the Chittagong University of Engineering & Technology (CUET).

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Abstract

Breast cancer has been one of the most dangerous types of cancer in recent years all over the world. Now-a-days not only women are affected, man are also being affected slowly. Various types of breast cancers are found according to National breast cancer foundation. Among all of these Ductal carcinoma is the deadliest one. The detection of Ductal carcinoma cancer at the very earliest stage can be wholesome to cure it. In the medical area, as well as other industries, computer vision may be quite useful. In this thesis,I'd like to demonstrate a Deep Learning-based computer-assisted technique for detecting and classifying breast cancer. A popular and useful pre-trained deep CNN model, Inception ResNet V2 is used for training.As classification of breast cancer from histopathology images are very difficult and complicated, so this very deep architecture is essential in this regard. The features obtained from this trained model is supplied to a multi-class Support Vector Machine (SVM) classifier to classify the cancer type. When compared to previous CNN models, the suggested framework's experimental findings showed improved recognition accuracy.

Keywords: Breast Cancer Detection and Classification, CNN models, Inception ResNet V2, multi-class SVM.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

In women all over the world, breast cancer is the most common type of cancer. In 2004, there were approximately 1.1 million cases reported. Breast cancer is the world's second most common cancer in general, the second most common cancer in women after skin cancer, and the sixth most common cause of cancer death. Men are also affected by breast cancer, and recent estimates estimate that in 2018, men will be diagnosed with over 2550 new cases of advanced breast cancer. (2019 Breast Cancer Statistics).

The overview of Breast Cancer and its type,incidence rate in USA will be described in this chapter, along with the inherent difficulties of this problem. This chapter would also explain the motivation for this research and how it contributes to the field.

1.1.1 Breast Cancer

Cancer is a broad term for a group of diseases characterized by the growth and invasion of healthy cells in the body by dysfunctional cells. Breast cancer begins as a cluster of cancer cells in the breast's cells, which may then infiltrate adjacent tissues or expand (metastasize) to other parts of the body. The most prominent form of breast cancer is ductal carcinoma, which develops in the lining of the Milk duct. Breast cancer that starts in the lobules of the breast is known as lobular carcinoma. Breast cancer that has spread to neighboring natural tissue from where it began in the breast ducts or lobules is known as invasive breast cancer. Both men and women are affected by breast cancer, but male breast cancer is rare. Breast cancer can spread outside of the breast via blood and

lymph vessels. If breast cancer has spread to other areas of the body, it is said to have metastasized. It is the root cause of cancer-related mortality in women under 65. There are two forms of Breast cancer including many types:Benign and Malignant.Here are described below:

Adenosis:Adenosis is a common benign breast disease that causes the lobules (milk-producing glands) to swell. 1In addition, there are more glands than normal. A lump, or multiple lumps, can form as a result of adenosis. Sclerosing adenosis is the name given to a disorder in which swollen lobules are also bent or twisted out of shape by scar-like fibrous tissue.

Fibroadenomas:Fibroadenomas are glandular and stromal (connective) tissue-based benign (non-cancerous) breast tumors. Fibroadenomas are most common in women in their twenties and thirties, but they may strike anyone at any age. Since a woman has been through menopause, they appear to shrink.

Phyllodes tumors:Phyllodes tumors are rare breast tumors that begin in the breast's connective (stromal) tissue. Phyllodes tumors are most frequent in women in their forties, but they can affect women of any age. Phyllodes tumors are more common in women with Li-Fraumeni syndrome (a unusual, hereditary genetic condition). The majority of phyllodes tumors are benign (non-cancerous), but approximately one out of every four of these tumors is cancerous.

Tubular breast cancer:Tubular breast cancer, is a form of invasive breast cancer. Cancer cells have the ability to migrate to other areas of the body in this way. Tubular breast cancer, on the other hand, is less likely to develop than other forms of invasive breast cancer. Tubular breast cancer is a form of invasive breast cancer that is relatively uncommon. It is more frequent in women over 50, but it can affect someone at any age. It's extremely common in the United States.

Ductal carcinoma:Ductal carcinoma in situ refers to cancerous cells that are exclusive to the lining of milk ducts and have not extended through the duct walls into adjacent breast tissue (DCIS). If ductal carcinoma in situ lesions go untreated, cancer cells may break through the duct and migrate to the surrounding tissue, resulting in invasive breast cancer. DCIS is the most prevalent form of noninvasive breast cancer in the United States, with around 60,000 new cases

diagnosed each year. Ductal carcinoma in situ accounts for around one out of every five new cases of breast cancer.

Invasive lobular carcinoma:Invasive lobular carcinoma is a form of breast cancer that starts in the milk-producing glands (lobules) of the breast and spreads to the lymph nodes and other parts of the body after breaking out of the lobule where it started.

Papillary ductal carcinoma:This cancer is very rare, making up less than 1% of all invasive breast cancers. The majority of these tumors are found in elderly, postmenopausal people. These cells imitate tiny fingertips or papules under a microscope. Papillary breast cancers are usually rare, and they test positive for estrogen and/or progesterone receptors while being negative for the HER2 receptor.

Mucinous ductal carcinoma: Breast cancers of this kind account for less than 2% of all breast cancers. These cancer cells are surrounded by mucus, according to microscopic examinations. Mucinous ductal carcinoma occurs in the milk duct of the breast, like other forms of invasive ductal cancer, before spreading to the tissues around the duct. This disease, also known as colloid carcinoma, often affects women after they have gone through menopause.

1.1.1.1 Breast Cancer Incidence Rate in USA Country

According to National Breast Cancer Foundation, Inc :

- In the United States, women are expected to be diagnosed with 276,480 new cases of invasive breast cancer and 48,530 new cases of non-invasive (in situ) breast cancer in 2020[1].

- Breast cancer is diagnosed in 64% of patients at a localized stage, with a 5-year survival rate of 99%.

- In the United States, one out of every eight women will grow breast cancer during her lifetime[2].

[1] `https://www.tallahassee.com/story/life/wellness/2020/10/12/get-facts-fight-back-during-breast-cancer-awareness-month/5955506002/`

[2] `nationalbreastcancer.org/wp-content/uploads/2020-Breast-Cancer-Stats.pdf`

• At the time of diagnosis, about 64% of breast cancer patients have localized disease, 27% have regionalized disease, and 6% have remote (metastatic) disease.

• Except for skin cancers, breast cancer is the most prevalent cancer in American women. Breast cancer is expected to account for about 30% of all current cancer diagnosis in women this year[3].

• Breast cancer would kill an unprecedented 42,170 people in the United States this year.

• Breast cancer kills about one in every 39 people (3%)[4].

• Breast cancer is the second leading cause of cancer mortality in women,after lung cancer,accounting for 15% of all cancer deaths.

• In the United States,an estimated 2,620 men will be diagnosed with breast cancer this year, with about 520 dying.

• Men are more likely than women to be diagnosed with early regional or distant-stage breast cancer (51% versus 36%), which is likely due to delayed diagnosis due to a lack of understanding.

• In the United States, there are over 3.5 million breast cancer survivors[5].

• There were an estimated 375,900 fewer breast cancer deaths due to early diagnosis and improved breast cancer awareness (Note: Report contrasts the past decade with this data estimated for 2017 – evidence for this year has not been released)[6].

• Invasive breast cancer accounts for 81% of breast cancer diagnoses in the United States, with a 5-year survival rate of 91 percent.

[3] https://www.cancer.org/cancer/breast-cancer/about/how-common-is-breast-cancer.html.

[4] https://www.cancer.org/cancer/breast-cancer/about/how-common-is-breast-cancer.html.

[5] https://www.cancer.org/cancer/breast-cancer/about/how-common-is-breast-cancer.html.

[6] https://www.facebook.com/WCWinchester/posts/october-is-breast-cancer-awareness-month-the1703004593201357/

1.2 Design Overview

Breast cancer is one of the leading causes of death in women. In recent years, breast cancer screening has received a lot of coverage, with the aim of avoiding it at an early stage. A comparison-based analysis of multiple deep convolutional neural network (CNN) based classification models for diagnosing of the affected breast cell is also provided. Different Convolutional Neural Network architectures were used to take a labeled (benign/malignant) input image and highlight the visual patterns, then use those patterns to differentiate between non-cancerous and cancer-containing tissue, similar to how digital staining highlights image segments important for diagnostic decisions.As a result,the proposed scheme depicted in Figure 1.1 offers a high-level overview of a useful classification model for identifying whether breast tissue is benign or malignant.

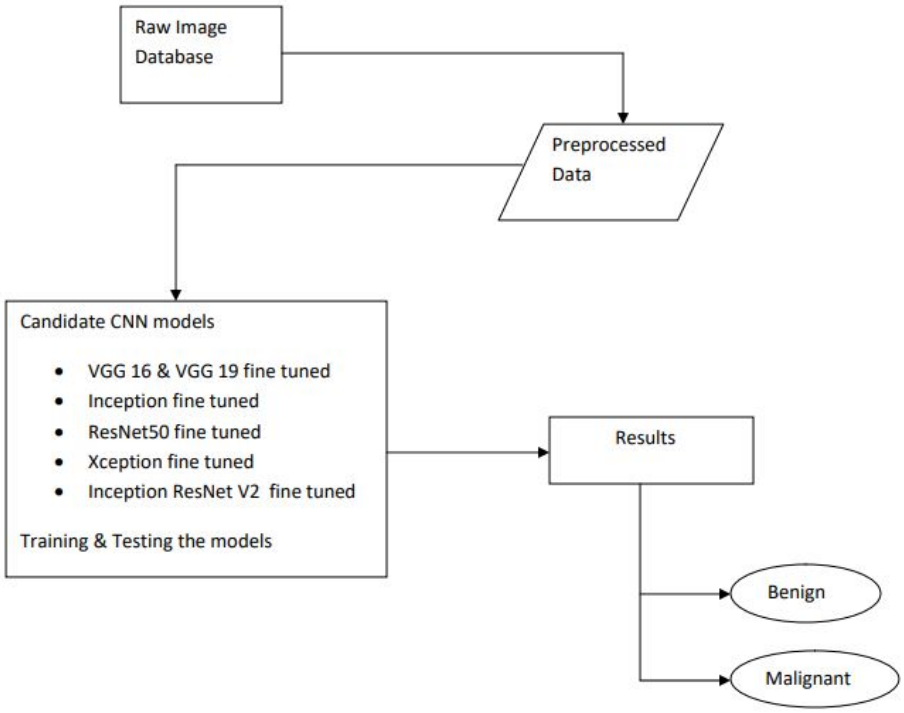


Figure 1.1: Overview of proposed work

1.3 Difficulties

Breast cancer is one of Bangladesh's most prevalent and deadly cancers, accounting for 69% of all cancer deaths in women. It has recently become a massive

burden. Breast cancer occurred at a rate of around 22.5 per 100000 in females. Breast cancer has the highest incidence rate (19,3 per 100,000) in Bangladeshi women ages of 14 and 44 as compared to other types of cancer. In reality, it has become disturbing due to a lack of knowledge, a lack of trust in medical care, social stigma and fear of cancer treatment, and a lack of socioeconomic infrastructure.In reality, it has become disturbing due to a lack of knowledge, a lack of trust in medical care, social stigma and fear of cancer treatment, and a lack of socioeconomic infrastructure. According to a morality study conducted in 2010 by Bangladesh's National Institute of Cancer Research and Hospital, 87 percent of new cases of breast cancer were identified as stage III+, indicating that the cancer has spread to other parts of the body. Some major difficulties are encountered here.

1.Image preprocessing and segmentation are tough due to presence of various resolutions in dataset.

2.It is essential to provide high-quality images of breast screening in order to identify cancers at an early stage.

3.Due to the difficulty of examining these tissues at low magnification, it is difficult for an automated CAD system to understand or discern distinctive features from images of varying magnifications in order to make a differential diagnosis.

4.Due to a complex and costly data processing process, the dataset in the medical context typically only contains a few samples. As a consequence, it's incredibly difficult to find a suiable, massive-scale, well-organized dataset.

5.The implementation of a comprehensive computer-aided diagnostic (CAD) method is hampered by unbalanced and limited data sizes.

6. Since histopathological images have rotation and reflection symmetry, if proper augmentation techniques are not chosen based on dataset, it is always possible to remove any inherent properties from the picture.

1.4 Application

Still now in this modern era,people are affliated with social barriers and prejudice.Women in the village are afraid of facing treatment due to either lack of awareness or trust issues. Medical officers,clinicians or technicians can easily apply computer aided system to mitigate the spread of the disease.They might easily detect the affected tissues at very earliest stage.Rural people can also enjoy the zest of this modern technology.

1.5 Motivation

Many things motivate me to take up this topic as my thesis.

Sufferings of women:Every year thousands of women loss their lives because of this dreadful disease.Some get to know after the spreading of the cancer all over the breast tissues.As a result,they have to undergo serious surgery of cutting of their breasts.

Early Detection can save live:Cancer is that type of disease which spread very easily and fastly.Just one minute can save anyone's life. In medical science early detection is very important.

1.6 Contribution of the thesis

Every thesis or research work has a specific goal. It can be defining or using a new approach or improving the current ones. The aim of this study was to reliably and effectively diagnose breast cancer. The goal of the proposed thesis work mentioned in the following:

1. To detect cancerous cell more accurately using new methodology.
2. Extraction of features from images by implementing Inception ResNet v2 CNN model.
3. Implementing SVM classifier to carry out classification.

4. Evaluation of overall performance of proposed methodology through simulation.

5. Performance comparison with other methodologies.

1.7 Thesis Organization

The thesis' structure can be summarized in the following points:

- Chapter 2 summarizes current research in the field of breast cancer diagnosis and classification.
- The proposed technique for detecting and classifying breast cancer is described in Chapter 3. A Inception-ResNet model is developed in the proposed system, and an SVM classifier is used to classify cancer types.
- The working dataset is defined in Chapter 4 along with an overview of the output indicator for the proposed system.
- The overall overview of this study work is presented in Chapter 5, along with several possible suggestions.

1.8 Conclusion

This chapter provides an outline of breast cancer diagnosis. This chapter also contains a review of breast cancer and its complications. This section also contains information about the work's motivation as well as the contributions made. The current situation of the problem will be discussed in the following sections.

Chapter 2

Literature Review

2.1 Introduction

Breast cancer is the most prevalent cancer in women all over the world. Owing to new surgical procedures and cutting-edge devices, battling breast cancer has never been simpler. Breast cancer screening is an effective way to follow up on an early diagnosis that may improve the chances of a successful treatment. According to the World Health Organization(WHO), breast cancer was the second most prevalent cancer in 2012.The area of breast cancer is being researched to a great degree. Regular consultation and detection of breast cancer can be performed with effective predictive systems depending on the volume of blood that can be collected in blood analysis [1, 2].

2.2 Related Literature Review

Spanhol et al. [3] employed AlexNet,CNN architecture for classifying entire slide histopathological images and acquired 84–90% accuracy.

This paper [4] reports on previous research on designing and enhancing machine learning for mammogram whole-image classification. They looked at seven different CNN architectures before settling on an approach that combines data augmentation and transfer learning with a CNN that improves classification accuracy.

Kowal et al. [5] shows comparison among different algorithms for the classification of nuclei segmentation as either benign or malignant.They used 500 images as dataset and analyze accuracies varying from 96% to 100%.

Lavanya et al. [6] used 10 fold cross validation, an ensemble decision tree approach

was used to boost the classification accuracies of the WDBC dataset. Cross validation is the most powerful and commonly used technique for measuring the performance of a machine learning model on a validation collection, according to the survey review [4].

As per the survey in [7],because of adaptability and simplicity, the KNN algorithm is the most commonly used classification technique in machine learning..

Saikia et al. [8] shows comparative assessment of CNN architectures for classification of breast FNAC images.They used VGG 16,VGG 19 and ResNet 50 architecture.

In [9],the author uses three pre-trained networks: VGG16, VGG19, and ResNet50 to explain comparative study and interpret their activity for magnification independent breast cancer classification.

The authors in [10],Tamura features and RBM, along with contrast corrections, were used to classify histopathological (BreakHis) breast images. They faced weight adjustment problem and training was slower.

This paper [11] proposed a deep learning algorithm for breast cancer detection and classification that is not as accurate as others and takes longer to compute.

M. M. Islam et al. [12] uses support vector machine, K-Nearest neighbors and 10-fold cross validation to get an accurate outcome and used wisconsin breast cancer diagonosis dataset. The approach doesn't provide better result both for training and testing. The method doesnot work well on complex dataset.

2.3 Conclusion

A thorough literature review is explored in this chapter. The suggested approach is detailedly explained in the following sections.

2.3.1 Implementation Challenges

In the study of histogram images, the magnification factor is extremely important. The magnification of an object is set so that it can be viewed easily. The histology

photographs provide a wide range of tissues, but analyzing these tissues at low magnification becomes difficult. Because acquiring a image at various magnifications introduces context diversity. As a result, learning or extracting distinctive features from photographs with varying magnifications to make a substitutional diagnosis becomes difficult for an automated CAD device. The use of photographs with the same magnification can be a way to minimize background variance, which has been favored in the majority of previous research [13, 14]. They classified images at a specific magnification stage. Previous studies have also considered images with several magnification variables, with different classifiers for each magnification [15, 16]. Implementation of such methods necessitates many phases of planning as well as prior awareness of the magnification element. A new magnification factor has placed a substantial cap on the network's efficiency, which could be a major flaw in the implementation of magnification-dependent approaches. As a result, a magnification-independent automated diagnosis device is needed, as well as the capacity to respond to new magnification factors.

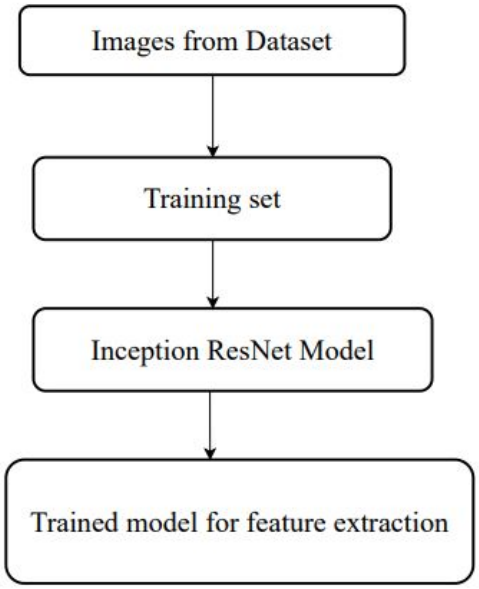
Chapter 3

Methodology

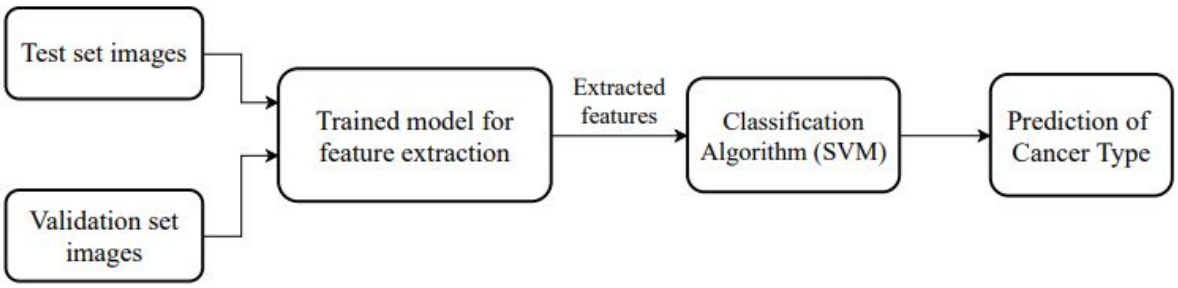
3.1 Introduction

Breast cancer is a dangerous tumor that develops as breast cells/tissues expand abnormally. In this chapter, some CNN architecture models are proposed for the identification of Breast Cancer and also comparative analysis is being analyzed here. Deep neural networks, among the numerous machine learning methods, are gaining a lot of attention because of their ability to automatically retrieve features and acquire representations. Another reason for its appeal is advances in computing power. CNNs, a common version of deep neural networks, have a wide range of applications in computer vision and are known for their shared weights and local networking properties. Until obtaining the image's class label, the CNN will use representation learning to eventually combine low-level features into high-level features. In this research, Inception ResNet model is introduced which is pretty well organized and efficient than other CNN's models. Also a multi-class classifier is used to carry out the classification process.

3.2 Overview of Breast Cancer Detection and Classification Framework



(a) Process flow of Training Algorithm



(b) Process flow of image classification

Figure 3.1: Steps of the proposed framework

Figure 3.1 shows the basic steps of the proposed approach for Detection and Classification of Breast Cancer framework. Firstly, the model is trained using training images set and then validate it using validation set images to check how well the model is performing. Here, Inception ResNet model is trained to represent features. Inception ResNet is a pretained CNN model. The parameters of the original deep architectures were kept unchanged. Each of the layers computes features. By combining these features, we achieve the feature vector set.

Breast cancer classification from histopathology photographs is difficult and time-consuming, so this very deep architecture is essential in this regard. Nowadays, a pre-trained architecture behaves like a function extractor by taking into account all previous activations to the network's last fully linked layer. Furthermore, these activations serve as a features vector for learning a classifier and executing classification. After training the model, test set images is loaded and feed to the trained model to extract features. Along with the label for each sample, the measured attribute vector collection is fed to a multi-class distinctive SVM classifier. The category of cancer is conveniently and quickly identified using this classifier.

3.3 Data Augmentation

The implementation of a comprehensive computer-aided diagnostic (CAD) method is hampered by unbalanced and small data sizes. Data augmentation is a method for enlarging a dataset in deep models to overcome the issue of small data space. Several common data augmentation techniques include flipping, scaling, cropping, rotation, noise injection, translation and interpolation. However, not all of the augmentation techniques used on real photographs will operate on medical images. As a result, depending on the dataset, selecting a data augmentation solution should be done carefully. Because histological images are symmetrical in rotation and reflection, there always happens risk of losing any inherent properties if other augmentation procedures are used, which would result in the loss of distinguishing features or details. As a result, only rotation is used as a data augmentation tool. The pictures are rotated around their base at three different angles: 90, 180, and 270 degrees. Another benefit of using the augmentation process is that it avoids overfitting, which is a major issue when it comes to effectively applying a machine learning model.

3.4 Convolutional Neural Network

A Convolutional Neural Network, or ConvNet/CNN, is a Deep Learning method used in image identification, classification, object identification, and face identification. CNN image classifications use an input picture, give priority to different aspects/objects in the picture (learnable weights and biases), then categorize it into one of many categories. When compared to other classification methods, the amount of pre-processing needed in a ConvNet is substantially smaller since its filters are hand-engineered with well-trained, having the capacity to learn these filters/characteristics. A ConvNet's architecture is identical to the neuronal connectivity pattern in the human brain. The computer sees an input image as an array of pixels and adjusts the image resolution accordingly, h x w x d(h = Height, w = Width, d = Dimension). In deep learning CNN models to train and test, each input image will travel through a sequence of convolution layers with filters (Kernals), Pooling, fully connected layers (FC), and Softmax function to identify an item with probabilistic values between 0 and 1. The complete flow of CNN is discussed in the figure below, which processes an input image and classifies the objects based on it. The ConvNet's goal is to compress the pictures to a format that is easier to handle while preserving critical properties that are required for accurate prediction. This is critical when designing an architecture that is capable of extracting features while also being adaptable to huge datasets.

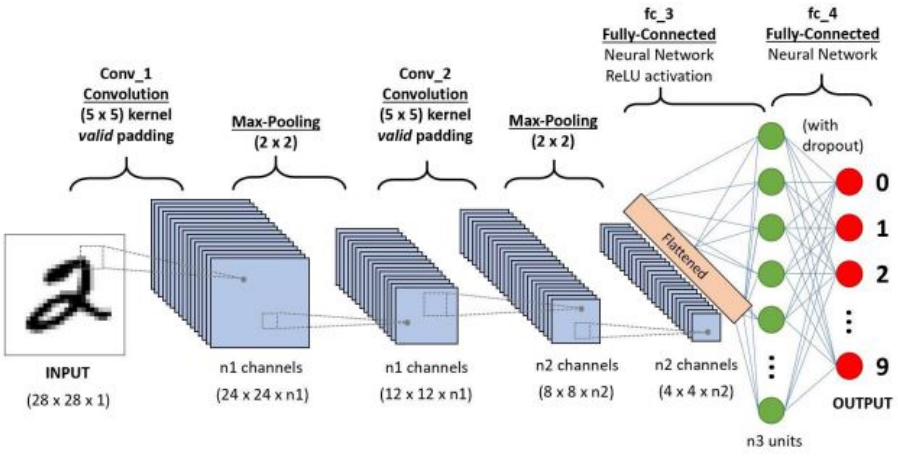


Figure 3.2: CNN Architecture

In the CNN, there are three sorts of layers. Convolution, pooling, and flattening are examples of layers.

3.4.1 Convolution Layer

Convolution is the initial layer in the CNN architecture, and it pulls features from an input picture. By learning visual features using tiny squares of incoming data, convolution preserves the link between pixels. It's a mathematical procedure that requires two inputs: a matrix of images and a kernel or filter.

- A volume of image matrices with the dimensions h*w*d.
- (fh*fw*d) is a filter.
- The volume dimension (h-fh+1)*(w-fw+1)*1 is output.

Stride and padding are the two other parameters of the convolutional layer. The Stride monitors the amount of kernel shift until the next output for that layer is determined. The Padding determines when additional dummy input points are applied to the boundary of the input layer so that the resultant output either maintains the same size after applying the filter or shrinks a from boundaries relative to the preceding layer.

3.4.2 Pooling Layer

If the images are too broad, the section for layer pooling will reduce the number of parameters. The Convolved Feature's spatial size reduction is accomplished by the Pooling sheet. By reducing the dimensionality of the data, less computational power is required to process it. It's also useful for achieving superior features like rotational and spatial invariance, which helps keep the model's training phase running smoothly. Max Pooling, Min Pooling, and Average Pooling are the three forms of pooling. Max Pooling returns the full value from the Kernel's portion of the image, as well as acting as a Noise Suppressant without affecting the layer's activation value. The minimum pixel value from the Kernel-covered portion of the image is returned by Min pooling. On the other hand, Average Pooling simply performs dimensionality reduction as a noise suppressing process, returning the

average of all the values from the part of the image protected by the Kernel. As a result, Max Pooling outperforms Average Pooling significantly.

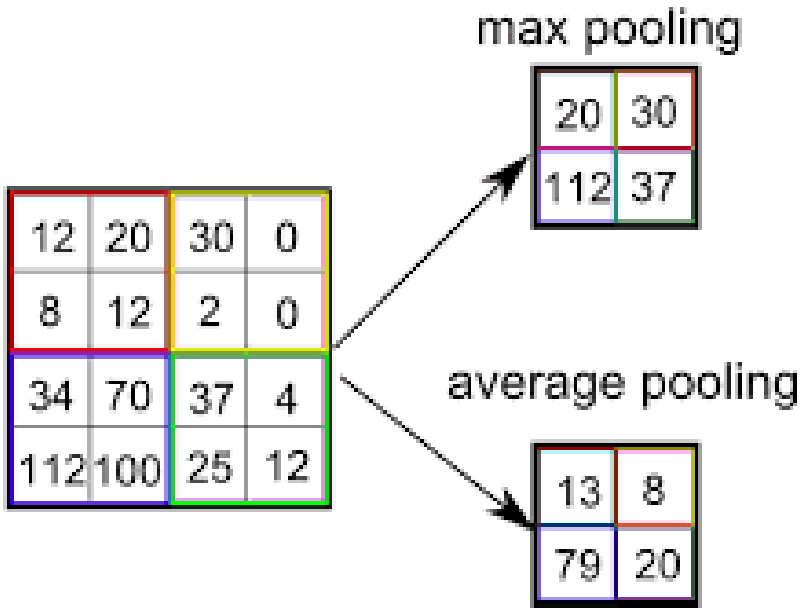


Figure 3.3: Pooling

3.4.3 Flattening layer

It converts the previous 2D or higher-dimensional layer into a 1-dimensional vector, which is better for feeding into the completely connected layer.

3.5 Non Linearity (ReLU)

ReLU stands for Rectified Linear Unit, which is a non-linear operation. f(x) = max(0,x) is the result . The goal of ReLU is to include non-linearity into ConvNet so that it may learn non-negative linear values from real-world data. Other non linear functions, such as tanh and sigmoid, can be employed in addition to ReLU. However, ReLU is superior to the others. It's a quick and easy way to access hidden layers. For any input x, the neuron output or activation function in a neural network is usually of the form f(x) = tanh(x) or the sigmoid function. Since they eventually map their input to an output between a fixed range such as [-1, 1], these neuron activation functions are saturating by design. Rectified

Linear Units are neurons that use non-saturating activation functions like f(x) = max(0,x) and can be used in a Convolutional Neural Network.

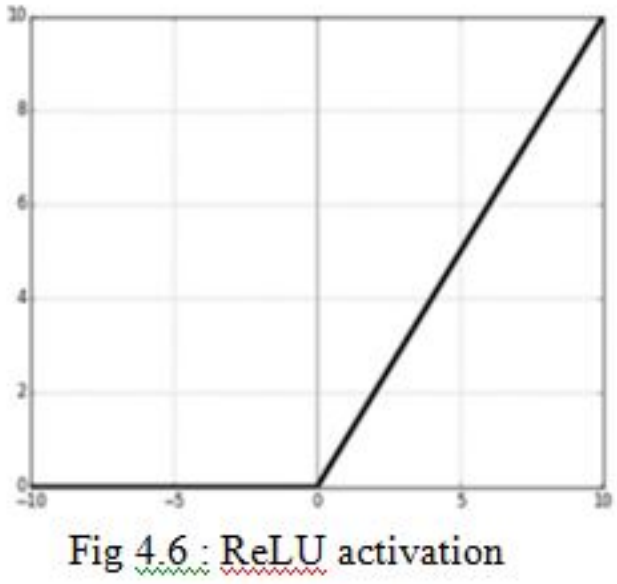


Figure 3.4: Non Linearity(Relu)

3.6 Fully Connected Layer (FC Layer)

Learning non-linear combinations of high-level features represented by the contribution of a convolutional layer using a Fully-Connected layer is a (usually) low-cost approach. In that area, the Fully-Connected layer is investigating a possible non-linear function. Now we'll flatten our input image into a column vector and convert it to a format that our Multi-Level Perceptron can read. Backpropagation is conducted to each round of training after the flattened output is given to a feed-forward neural network. Using the Softmax Classification approach, the model can discriminate between dominating and low-level characteristics in pictures across a number of epochs and identify them.

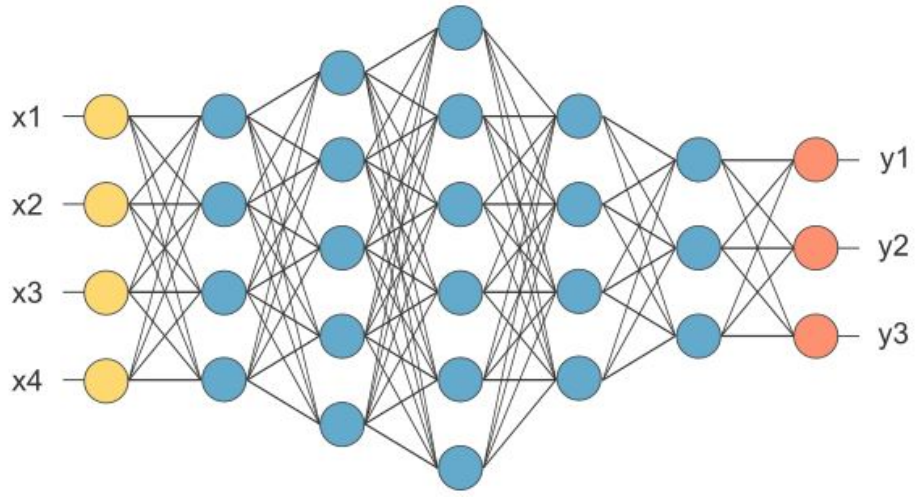


Figure 3.5: Fully Connected Layer

3.6.1 Dropout layer

Between fully connected layers, we can also use dropout layers. It shuns the contribution of every fraction of nodes from the previous layer during the training stage and proportionally dampens the activation during prediction by the same fraction. It's more likely that only a limited percentage of nodes in the secret layer will learn through training by updating the weights of the edges that link them, while the rest will stay "asleep." Dropout allows all the edges to learn in this case by randomly shunning all links from a certain fraction of nodes from the previous layer during the training point. Overall, this method prevents network overfitting by assisting in the classification of more unknown cases with greater accuracy during the testing period.

(a) Standard Neural Net

(b) After applying dropout

Figure 3.6: Dropout Layer

3.7 Softmax function

Softmax is an activation feature that converts a number variable into a probability vector, with the probabilities of each value equal to the vector's relative size. It's a mathematical expression. It's used to transform a neural network model's outputs from weighted sum values to probabilities that total to one. Each value in the softmax function's output denotes the chance of belonging to each class. Softmax is a feature that transforms the outputs of a neural network's last layer into a discrete probability distribution over the target groups. Softmax guarantees the probabilities are real-valued numbers with no negative values. Mathematically, this is defined as follows: $Softmax(x_i) = \frac{exp(x_i)}{\sum_j exp(x_j))}$

3.8 Loss function

The Loss Function is a crucial concept in Neural Networks because it is used to estimate the error of the network. It's a way of figuring out how well a particular algorithm models the data. The loss function would return a significant amount if forecasts were too far off from actual outcomes.

3.9 Learning rate

The learning rate, which controls how much the model changes in response to the predicted error each time the model weights are modified, is one of the most critical hyper-parameters to set for deep neural networks training. The method for calculating the learning rate is crucial. Training will be more successful if the learning rate is low, but optimization will take a long time since the steps towards the loss function's minimum are tiny. If the learning rate is large, training cannot converge or even diverge. Weight variations might be so extreme that the optimizer misses the bare minimum, exacerbating the loss.

$$W = W + \alpha * gradient$$

The learning rate,α determines how far we progress down the gradient. We are

taking larger actions if the values are higher. Smaller values of α might cause modest movements. If α is null, the network will be unable to do any actions (since the gradient multiplied by zero is zero). After that, a network is conditioned at a constant learning rate for a set number of epochs.

While this strategy may be effective in some circumstances, it is frequently more useful to slow down our learning pace over time. Instead of maintaining a steady learning rate throughout, we may slow down our learning rate, enabling our network to take smaller steps. Our network may now descend into portions of the loss landscape that are "more optimum" that would otherwise be overlooked altogether by our learning rate because of the lower learning rate.

Learning rate=init lr*(1/1+decay*iterations)

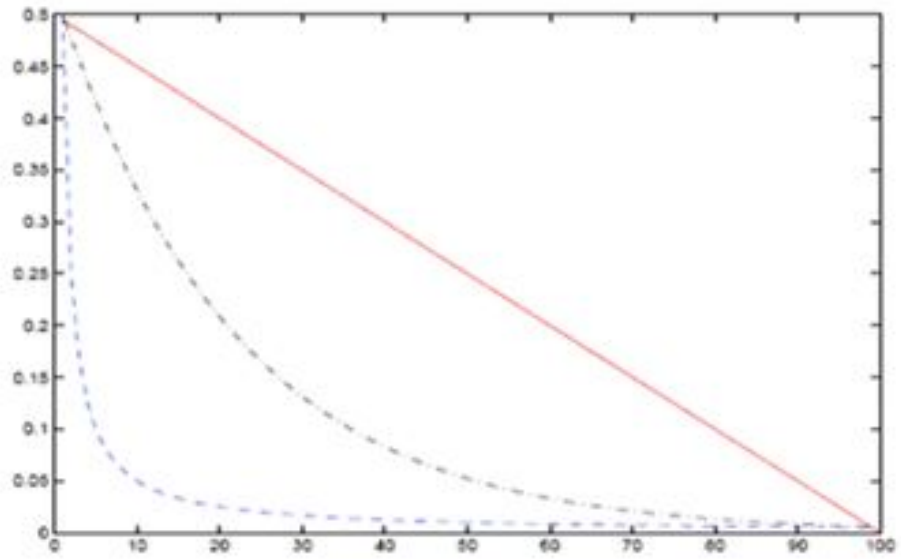


Figure 3.7: Linear Decay Learning Rate

3.10 CNN Architectures

3.10.1 VGG

VGG is a convolutional neural network architecture introduced by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition"[17]. It is regarded as one of the best vision model architectures to date, and it was utilized to win the 2014 ILSVR (Imagenet) competition.

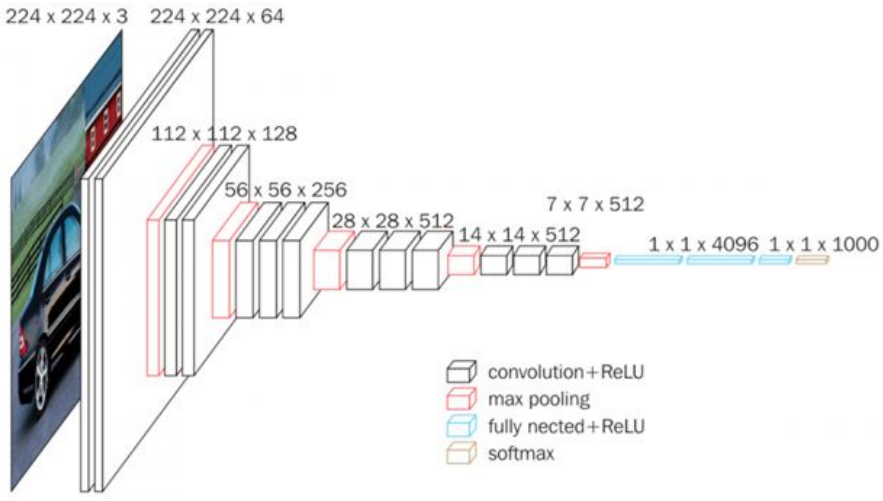


Figure 3.8: A visualization of the VGG architecture

The biggest differentiating aspect of VGG16 is that instead of creating a large number of hyper-parameters, they concentrated on having 3x3 stride 1 filter convolution layers while keeping the same padding and maxpool layer as the 2x2 filter stride 2. It maintains the same order in the architecture for the convolution and max pool layers. It starts with two completely linked layers, then a softmax for output. The number 16 in VGG16 refers to the fact that there are 16 layers with varying weights. With around 138 million (approx) parameters, this network is fairly large .

The architecture of VGG-16

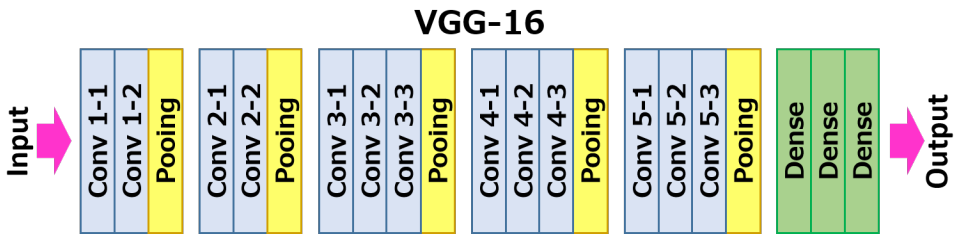


Figure 3.9: VGG-16

3.10.1.1 VGG-19

VGG19 is a VGG model that consists of 19 layers in total (16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer).

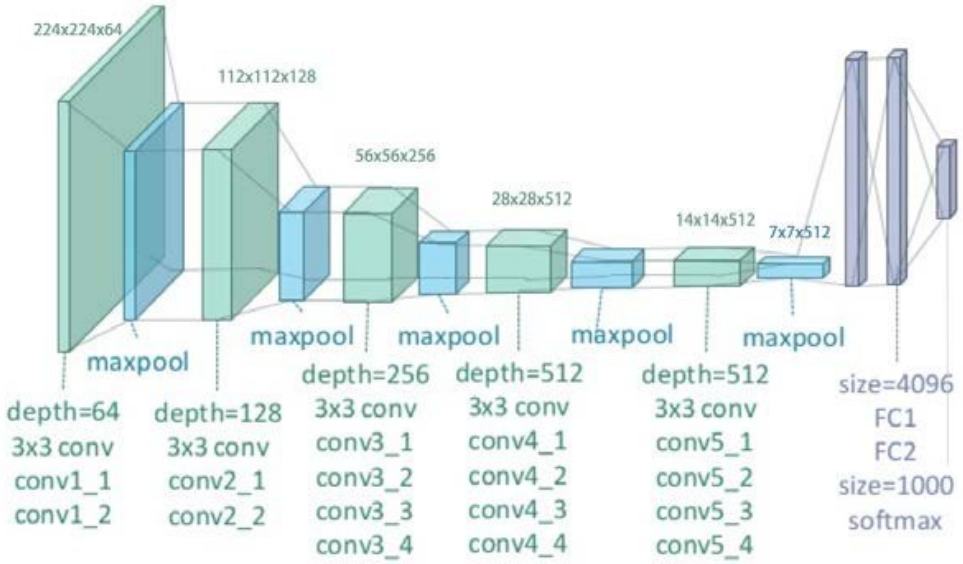


Figure 3.10: VGG-19[18]

3.10.2 ResNet

Since deep neural networks take a long time to train and are prone to overfitting, a Microsoft team devised a residual learning framework to speed up the training of networks that are considerably deeper than previously used networks. The ResNet architecture was first proposed by He et al. in their 2015 article, "**Deep Residual Learning for Image Recognition**", showing that extremely deep networks can be trained using regular SGD (and a rational initialization function) by using residual modules:

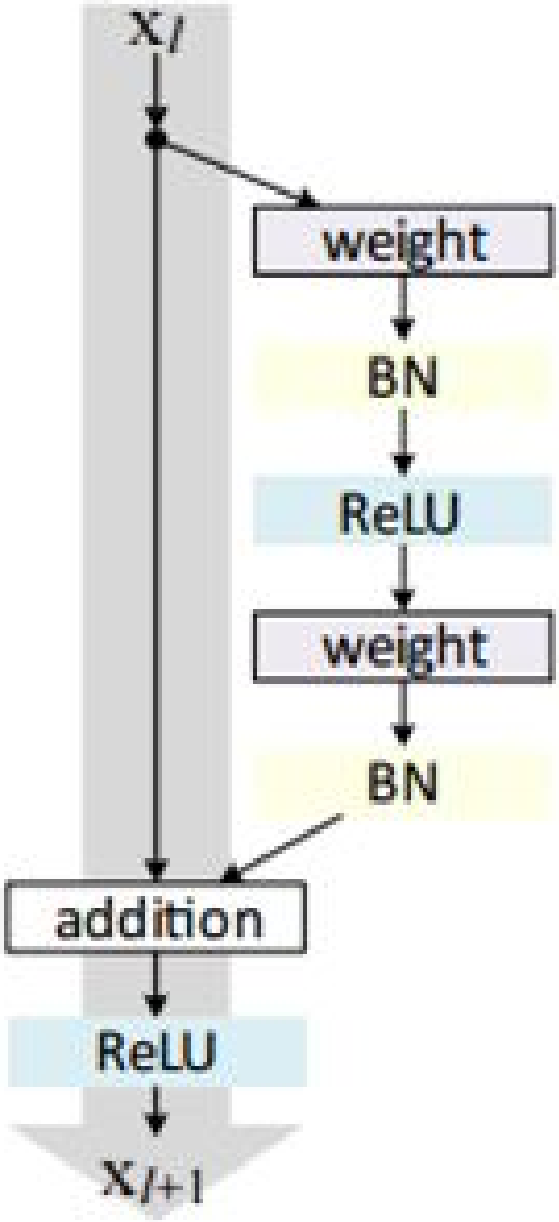


Figure 3.11: The residual module in ResNet as originally proposed by He et al. in 2015

The Residual Network was used to tackle the problem of the vanishing/exploding gradient in this design. This network employs a mechanism known as skip connections. The skip connection bypasses a few stages of training and links straight to the output. The network is permitted to match the residual mapping rather than enabling layers to learn the underlying mapping. Instead of using H(x) as the original mapping, use F(x) := H(x) – x, which gives H(x) := F(x) + x.

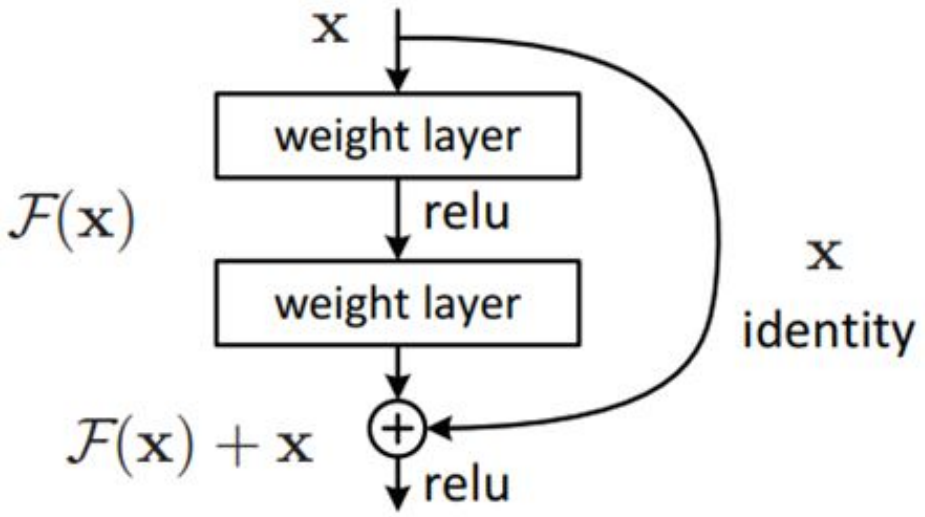


Figure 3.12: a residual block

Network Architecture: This network uses a 34-layer simple network design inspired on VGG-19, followed by shortcut connectivity. As a result of the shortcut linkages, the architecture is turned into a residual network.

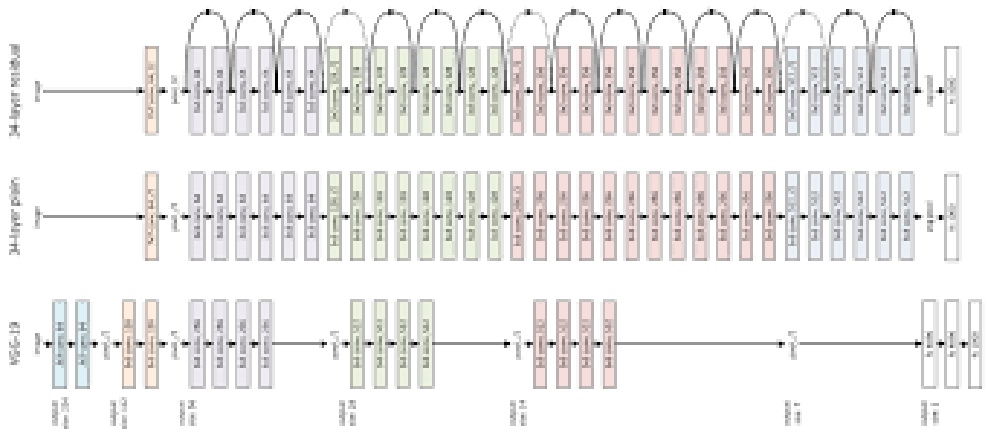


Figure 3.13: ResNet architecture[19]

ResNet is significantly deeper than VGG16 and VGG19, however owing to the use of global average pooling rather than fully-connected layers, the model size is slightly less – ResNet50's model is only 102MB.

3.10.3 Inception V3

The “Inception” micro-architecture was first introduced by Szegedy et al. in their 2014 paper[20].

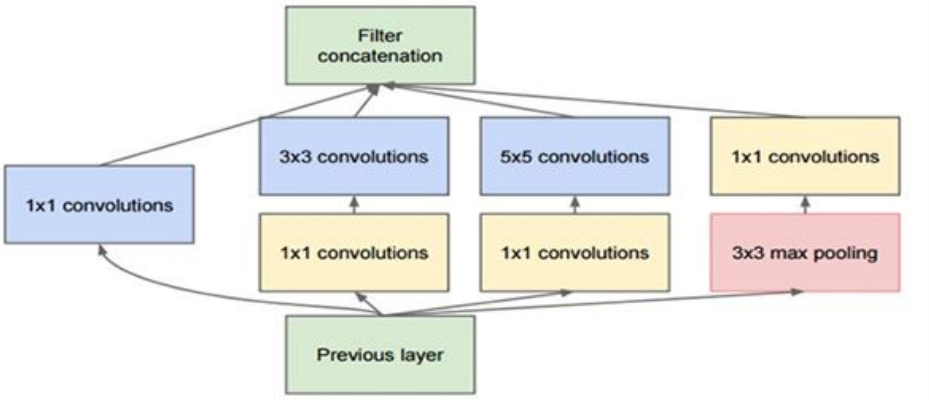


Figure 3.14: The original Inception module used in GoogLeNet

The inception module’s motto is to serve as a "multi-level function extractor" by computing 1×1, 3×3, and 5×5 convolutions within the same network module, then stacking the output of these filters along the channel dimension until feeding into the next layer. The initial version of this architecture was known as GoogLeNet, but subsequent manifestations have simply been referred to as Inception vN, where N refers to the Google version number. By changing previous Inception architectures, Inception v3 primarily focuses on burning less computational power. This concept was first suggested in the paper “Rethinking the Inception Architecture for Computer Vision” in 2015. Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, and Jonathon Shlens collaborated on it.The motivation for Inception-v2 and Inception-v3 is to use factorisation approaches to prevent representational bottlenecks (which involves greatly minimizing the input dimensions of the next layer) and to provide more effective computations.

3.10.4 Inception-ResNet-v2

The Inception-ResNet-v2 model is a variant of the Inception V3 model, and it is significantly more detailed than the previous Inception V3. The Inception-ResNet-v2 architecture is more reliable than the previous version.

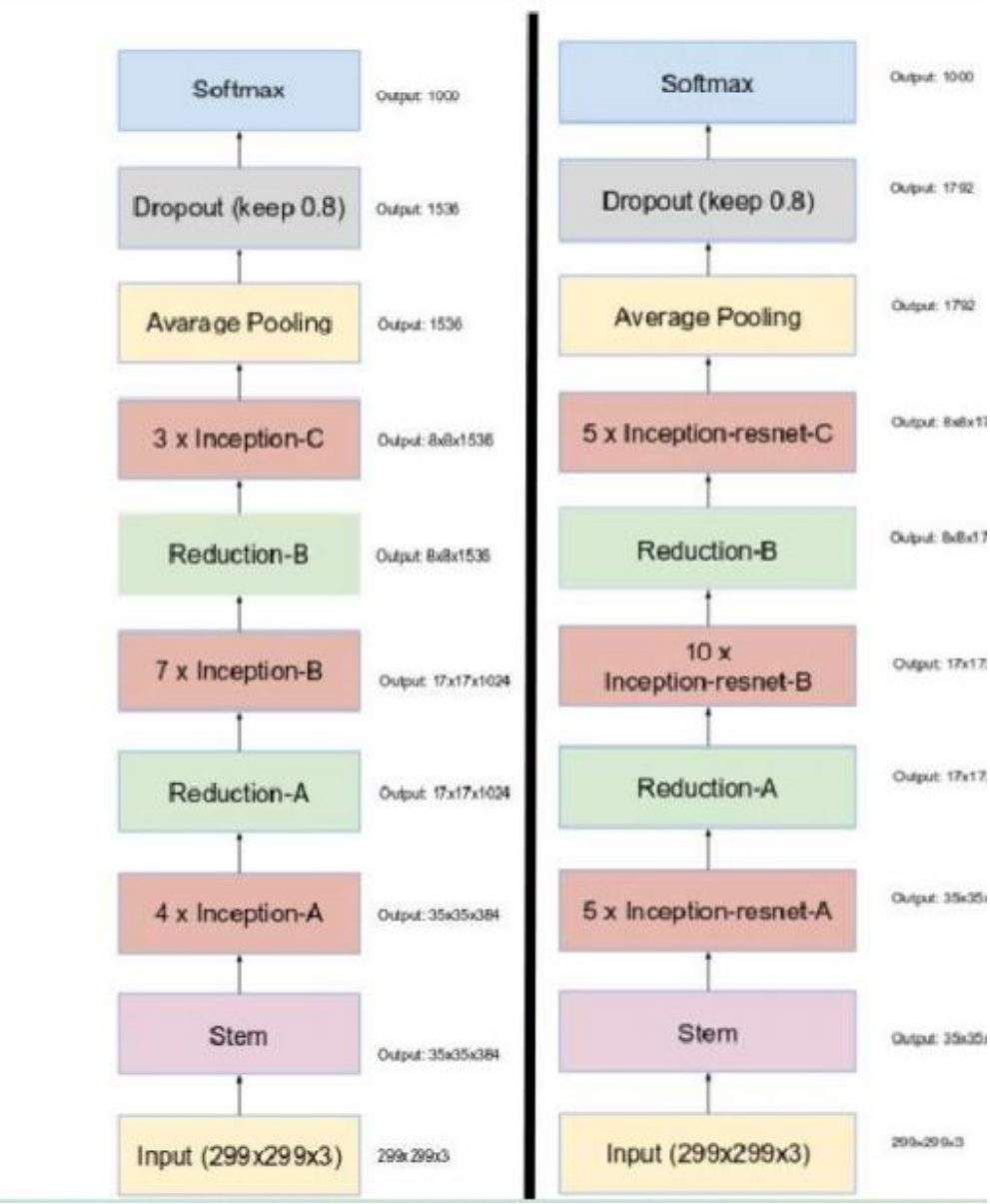


Figure 3.15: The layout of Inception v4 is seen on the left. The layout of Inception-ResNet is seen on the right[21]

The main motto of this thesis work is to establish a pretained Inception-ResNet-V2 model along with other models that mentioned above to check comperative analysis in term of accuracy.

3.11 Classification

Classification is the process of allocating an unknown sample to a predetermined class or type based on the training data used to train the classifier. The Support Vector Machine (SVM) classifier, among many others, has recently gained

prominence in recognition tasks. SVM is a classification system that was created specifically for binary classification.This method, on the other hand, may be utilized to solve a multi-class issue like the one in this research.

SVM is a well-known supervised machine learning technique for classification and regression problems. When maximizing the margin, SVM's main purpose is to determine the optimal hyperplane for linearly separating data points in two components.

We have a total of l training samples, each of which is of D dimension ,viewed as (xi, yi) where xi is the feature vector of sample i and has labels of either yi=+1 or yi=-1 class, and our examples are linearly separable. Then we have our training data in the form of,

$$\{x_i, y_i\} \qquad where \qquad i = 1....L, y_i \in \{-1, 1\}, x \in \mathcal{R}^{\mathcal{D}}$$

The hyperplane w.x+b=0 can be showed as :

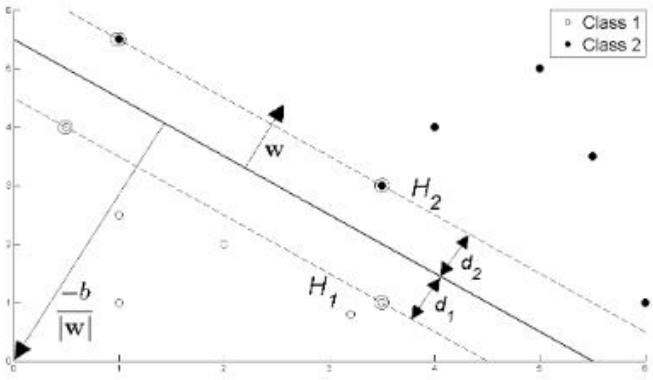


Figure 3.16

The goal of the SVM is to orient this hyperplane as far away as possible from the nearest member of both groups. Support vector instances are the closest to the ideal hyperplane. From the figure Formula of SVM can be derived as:

$$w * x_i + b >= 1 \qquad when \qquad y_i = +1$$

$$w * x_i + b <= 1 \qquad when \qquad y_i = -1$$

where w is the weight factor and b is the bias. Two hyperplanes H1 and H2 pass through the support vectors of the +1 and -1 groups, respectively, as seen in Figure 3.18.

w.x+b=-1 :H1

w.x+b=1 :H2

Given that we're dealing with roughly 8 different types of Breast cancer, this is clearly a multi-class problem. The multi-class problem can be solved using the same basic principle as the binary class problem.Firstly, we have to divide the multi-class classification dataset into several binary classification datasets and apply a binary classification model on it. Two approach can be used such as: One-vs-Rest and One-vs-One strategies. A multi-class classification dataset is broken into binary classification problems using one-vs-one. Unlike the one-vs-rest method, which divides the dataset into one binary dataset for each class, the one-vs-one method divides it into one dataset for each class versus all other classes. In One vs One , K(K 1)/2 binary classifier functions are introduced where one for every possible pair of classes. In this thesis, is constructed using One Vs One method is used to construct multi-class SVM because it gives better accuracy by far. Nevertheless, as k(k-1)/2 classifier is constructed primarily, it gives overhead more than One Vs All.

3.12 Implementation

Implementation of breast cancer detection and classification is a challenging task. I have tried my best to implement it efficiently.

3.12.1 Implementation Tools

As shown below, the necessary tools to create this system may be classified into two categories: hardware and software.

- **Hardware Requirements**

  Personal Computer

- **System Configuration**
  - Windows 10 Pro Operating System
  - Core i5 2.60 GHz Processor
  - 4.00 GB RAM
  - 64 bit Operating System
  - Version 1703
- **Software Tools and libraries**
  - python 2.7.13
  - opencv 3.1.0
  - Google Colab
  - Tensorflow
  - Keras

3.12.2 Breast Cancer Detection and Classification Process

For this thesis work, BreakHis dataset is used as input images. Dataset is augmented using ImageDataGenerator class.Based on the dataset,only rotation can be performed. Image set is splitted into train,test and validation set.

No further approach is required because feature extraction is done automatically in the CNN model. For feature extraction, the Inception ResNet model is employed.

The model is now trained with images from the training set, and the best trained model is saved for feature extraction. The validation set is used to assess the model's quality.

Following the checking, the test set is fed into the model for feature extraction, followed by classification using the SVM classifier.

3.13 Conclusion

In this chapter, a methodology for Detection and classification of Breast Cancer framework is explained. For model construction, a CNN model Inception-ResNet-v2 is used. The 'One Vs One' encoding approach is used in conjunction with a multiclass SVM classifier for classification. A experimental setup of this project is also included. The experimental outcome interpretation of the proposed system is discussed in the following sections.

Chapter 4

Results and Discussions

4.1 Introduction

A full explanation of the suggested framework was provided in the preceding chapter. The performance of the suggested framework is examined in this chapter. A performance matrix would be use to evaluate the performance.

4.2 Dataset Description

The BreakHis database has been used to carry out this thesis, which has been assembled from the result of a survey conducted by PD Lab, Brazil within January 2014 to December 2014. Throughout the procedure of surgical (open) biopsy (SOB), breast tissues are taken as samples. Hematoxylin and eosin dye the samples, which are then produced using a traditional paraffin procedure that involves specimen penetration and embedment in paraffin. Images are captured using a Samsung high-resolution device (SCC-131AN) in conjunction with an Olympus BX-50 microscopic system with a 3.3-magnification relay lens. The RGB (three channel) TrueColor including 8 bits depth in each channel, coding scheme is used in these histopathology pictures. This archive includes 7009 images with a resolution of 700X460 pixels. A detailed overview of the BreaKHis database might be found in [16].Dataset can be collected from Kaggle[1]. The table 4.1 illustrates the picture distribution in four resolutions.

[1] `https://www.kaggle.com/ambarish/breakhis`

Magnification	Benign	Malignant	Total
40X	625	1,370	1,995
100X	644	1,437	2,081
200X	623	1,390	2,013
400X	588	1,232	1,820
Total	2480	5429	7909

Table 4.1: BreakHis Database

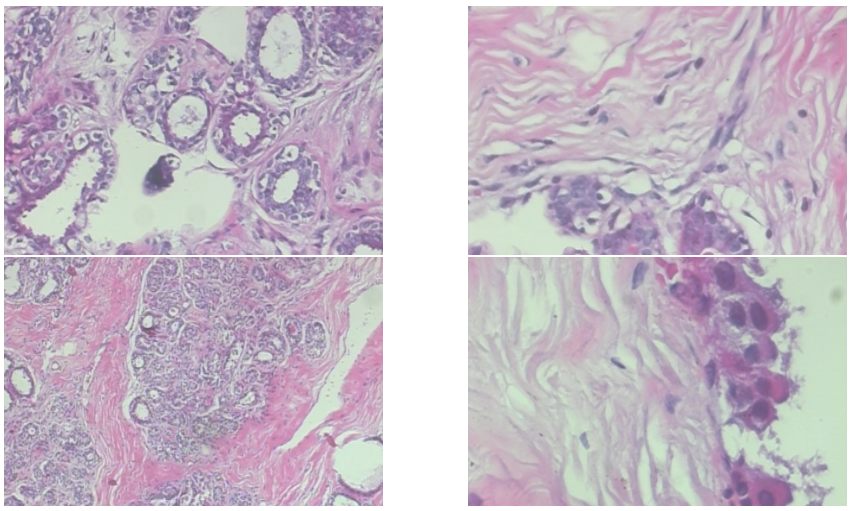


Figure 4.1: Breast Cancer Histopathological Images at four magnification levels (a) 40x, (b) 100x (c) 200x and (d) 400x from the BreakHis Dataset of a Patient Suffering from Adenosis (Malignant).

4.3 Evaluation of Framework

In [8],saikia et al. use VGG 16,VGG 19 and ResNet 50 model for featute extraction whose accuracy are given below table 4.2. On the contrary,Inception ResNet v2 model is used in this thesis and achieved accuracy 94% which is apparently better.

Model	Accuracy%	Loss
VGG 16	63.2	0.6395
VGG 19	60.84	0.8606
ResNet 50	79.61	0.3414
Inception ResNet v2	94	0.1132

Table 4.2: Classification accuracy of different CNN model

Table 4.3 shows accuracy of VGG 16, VGG 19, ResNet 50 from another paper [9]. Also here Inception ResNet v2 is comparatively better than the others.Overfitting

Model	Accuracy%	Loss
VGG 16	63.93	0.7356
VGG 19	50.27	0.7023
ResNet 50	79.83	0.3414
Inception ResNet v2	94	0.1132

Table 4.3: Classification accuracy of various CNN model

was the only factor for the network's poor results, which was caused by its unnecessarily large ability. As a means to reduce the network's active capacity and overfitting, further layers in the network could be frozen.

4.4 Evaluation of Performance

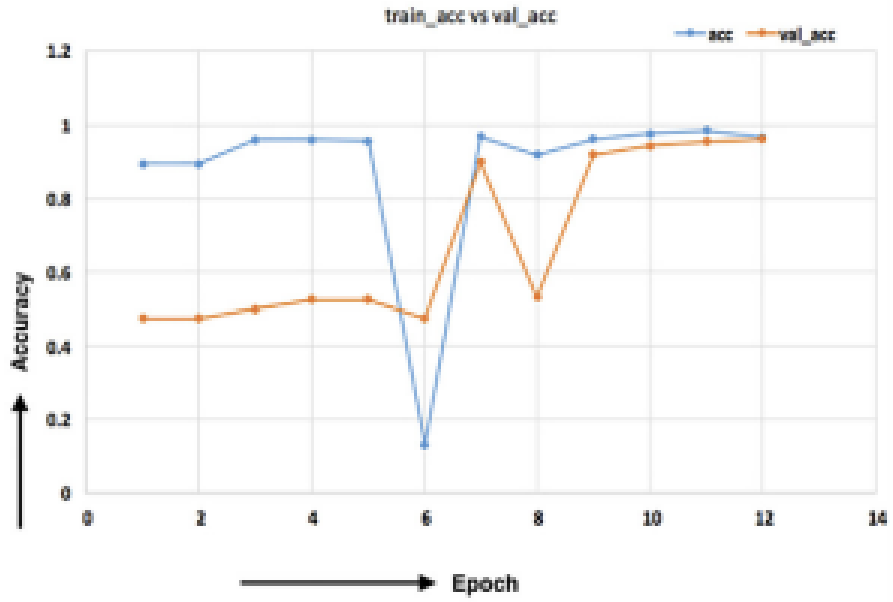


Figure 4.2: Accuracy in Training and Validation

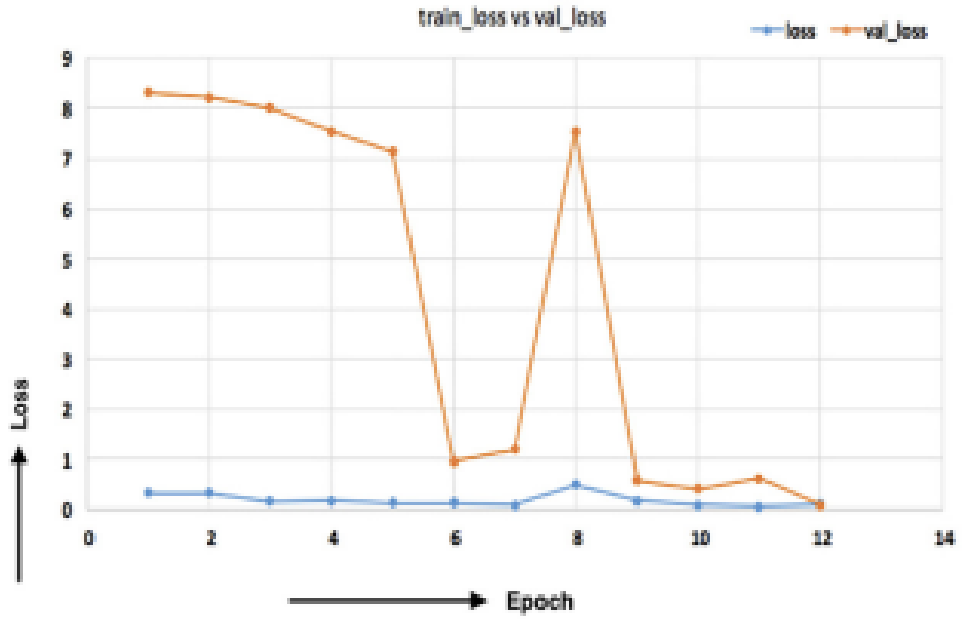


Figure 4.3: Loss in Training and Validation

Confusion Matrix

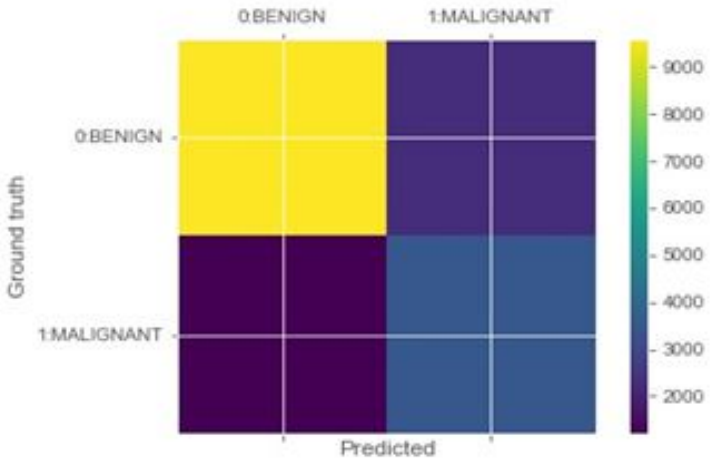


Figure 4.4: Confusion Matrix

- **True Positives (TP)**

- These are successfully predicted positive values, indicating that both the true and projected class values are yes.

- **True Negatives (TN)**

-These are the properly estimated negative values, indicating that the true and predicted class values are both no.

False positives and false negatives happen because the current class differs from the expected class.

- **False Positives (FP)**

–If the predicted class is yes, but the actual class is no.

- **False Negatives (FN)**

–When the predicted class is negative and the true class is positive.

Types of classes	
Benign	**Malignant**
C1 (adenosis): 444	C1 (ductal_carcinoma): 145
C2 (fibroadenoma): 1014	C2 (lobular_carcinoma): 142
C3 (phyllodes tumor): 453	C3 (mucinous_carcinoma): 135
C4 (tubular adenoma): 569	C4 (papillary_carcinoma): 560

Figure 4.5: Types of benign and malignant cancers, as well as their counts

		Predicted							
		Benign				**Malignant**			
			C1	C2	C3	C4	C1	C2	C3	C4
Actual	**Benign**	C1	70	8	1	3	6			
		C2	7	154	3	3	16	5	8	4
		C3	3		75		4		7	1
		C4		8		88		4	4	
	Malignant	C1	1	2	1	1	19	1	3	1
		C2		1	8			16	1	2
		C3		2		2	2	1	19	
		C4	2	2	8		12		10	80

Figure 4.6: count the number of anticipated and actual images for each class using proposed methodology

			Predicted							
			Benign				Malignant			
			C1	C2	C3	C4	C1	C2	C3	C4
Actual	Benign	C1	67	6	2	4	6	1	1	
		C2	9	143	6	7	15	5	10	5
		C3	4	2	68	1	5	2	6	2
		C4	3	6	1	2	3	5	2	2
	Malignant	C1	1	3	2	8	14	3	2	1
		C2		1	7	2	1	14	1	2
		C3	1	2	2	3	1	2	13	3
		C4	3	4	7	3	11	3	9	7

Figure 4.7: count the number of anticipated and actual images for each class using existing CNN ResNet model

Accuracy

The most efficient performance metric is accuracy, which is necessarily the number of correctly expected observations to all observations. One might believe that higher accuracy means model is best.

Accuracy= (TP+TN)/(TP+FP+FN+TN)

Precision

The ratio of accurately anticipated positive observations to total projected positive observations is known as precision. Precision = TP/(TP+FP) In our case, precision is about 86%.

Recall (Sensitivity)

The percentage of accurately predicted positive observations to all observations in the actual class is known as recall. Recall = TP/(TP+FN) In our case, recall is about 84%.

F1 score

The F1 Score is the weighted mean of Precision and Recall. As a consequence, all false positives and false negatives are taken into account in this ranking. F1 tends to be more useful than accuracy, despite the fact that it is less intuitive. This is especially true if the class distribution is unequal.Accuracy works best when the costs of false positives and false negatives are equal. It's advisable to consider both Precision and Recall if the cost of false positives and false negatives differs. The F1 score in our case is 0.85.

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

4.5 Conclusion

The consequences of a breast cancer diagnosis is depicted in this chapter. The effectiveness of the suggested framework is also discussed. The data reveal that the recommended methodology is more precise. The next chapter draws a close to this study project.

Chapter 5

Conclusion

5.1 Conclusion

My primary goal was to create a system that can identify and classify breast cancer at the very early level, which may helpful to reduce the growing rate of cancer and also death rate due to cancer. If breast cancer is detected early enough, it could be curable, although in most cases, treatment is straightforward. I tried my best to develop the system with efficiency. Physicians and technicians may use it to make a more precise diagnosis of breast cancer. The proposed method could be more effective in remote areas where medical professionals may not be available.

In this thesis, the Breast Cancer Detection framework is proposed based on the CNN model.For this work, images are considered as input from image dataset. Data augmentation technique is performed and the splited them into training,testing and validation set.

Feature are extracted using CNN model. Inception ResNet v2 is used as feature extractor. It is then fed to a multi-class SVM classifier. One Vs One encoding method is used here.

For comparison, other CNN model such as VGG 16, VGG 19, ResNet 50 is also constructed. From above both table,it is found that Inception ResNet v2 is tad bit better than other model in performance evaluation of fully trained network. Two paper references are included here in terms of comparison assessment. There VGG 16, VGG 19, ResNet 50 were used as model. The proposed framework might be used as a jumping off point for further research.

5.2 Future Work

As Breast Cancer detection still remains an open problem, always there remains a chance of occuring of false negative cases. The proposed work is in its medium stage and tried to have as many as improvement possible from more parameter calculation to tuned the network. Hence, to achieve better results more research needs to done.Next time,I would try to use spatial pyramid pooling with Inception ResNet v2 as this combo work very well proven by recent research.Fine-tuning at the layer level, a larger dataset, sophisticated data augmentation techniques (such as conditional generative adversarial networks (GANs) and a deep picture style weight initialization techniques) and the different weight shift techniques (for example, Xavier, He, MSRA, and Gaussian distribution) in full training of network are some approaches that can be pursued in the future aspects of the research.

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