笔杆检测报告单（全文标明引文）

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原文内容

UNDERGRADUATE PROJECT PROPOSAL

Project Title: Inception-Enhanced Depthwise CNN of Residual Learning for Breast Cancer Diagnosis

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Module Code: CHC 6096

Module Name: Project

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Table of Contents

1Introduction

1.1Background

Breast cancer is the one of the most fatal diseases so far in the world. It is said by American cancer society surveillance that one out of eight women is affected by it [1]. According to statistics recorded by World Health Organization (WHO)[2] among the 9.6 million cancer-related deaths,627,000 females passed away due to breast cancer in 2018, in addition, WHO had also predicted that 43,600 women would die from breast cancer in 2021[3], which indicates that breast cancer remains the leading cause of women death.

Breast cancer is similar to other type of cancer which can be early stage (Benign) and later stage (Malignant). Once the disease reached malignant stage, cancer might spread to other parts of the body which leads to catastrophic results, therefore, it is crucial to detect breast cancer at early stage in order to provide appropriate treatment [4]. Mammography serves as a common approach for breast cancer detection which the picture is normally taken through Magnetic Resonance Imaging (MRI), X-Ray, and Ultrasound, other methods rely on tissue sample from affected area of breasts and complete the diagnosis and classify by microscope [5].

It is unfortunate that the diagnosis still face troubles. Manual diagnosis through medical images or microscope is time-intensive, expensive and prone to errors, as symptoms are likely to be overseen [6]. For example, ultrasound breast cancer images detection highly depends on the experience, capability and knowledge of radiologists and diagnosticians [7], which most of the small hospital might not be equipped with.

Therefore, development and deployment of a deep learning based system focused on classification and diagnosis of breast cancer is the main goal of this project so as to avoid man power wastes, applying more targeted treatment to patients, lowering death rate, save more lives.

1.2Aim

Various models in deep learning diagnosis utilize specific single model, however, by doing so, there are chances that flaws of specific models could affect the performance in a negative way. To eliminate the drawbacks and maximize the performance, this project aims at develop and deploy a novel CNN model including Inception-ResNet model to classify the levels of breast cancer. Based on Wang et al.[8], Inception-ResNet possess a remarkable balance between model accuracy and resource efficiency.

1.3Objectives

The project will collect breast cancer symptom data from online sources, utilizing datasets like BreakHis, IDC, and mini-DDSM. BreakHis has benign and malignant categories with 9,109 microscope images from 82 patients. IDC contains 198,738 negative and 78,786 positive invasive carcinoma images. The data will be divided into training and testing sets for four different scaled images, with an 80% portion allocated for training and a 20% portion for testing. Within the training set,10% of the images will be randomly selected as a validation set. It is essential to include both benign and malignant samples in both sets.

The project aims to build a Depthwise-Inception-ResNet-Attention model, with hyperparameter adjustments: batch size of 4, learning rate at 0.001, dropout between 0.3 to 0.5. For binary classification, the output layer will use "sigmoid" activation,"Adam" optimizer, and "Binary-Crossentropy" loss function.

In addition, the evaluation of the model will include metrics such as "Accuracy" and "Loss." Moreover, performance will be assessed using "Precision,""Recall,""F1-Score,""AUC-ROC,""AUC-PR,""Specificity,""Sensitivity," and the "Confusion Matrix.

Lastly, the project will be deployed through a website which allows uploading medical pictures of breast cancer, then give the classification results.

1.4Project Overview

1.4.1Scope

Convolutional Neural Networks (CNNs) were introduced to medical image processing in the 1980s and have become the dominant approach in this field [9]-[10]. While Inception-ResNet delivers impressive performance, models not tailored to specific scenarios often encounter issues like gradient vanishing, local minima, and overfitting. Therefore, enhancing Inception-ResNet through the incorporation of depthwise operations is imperative. By using depthwise operations, it will reduce the parameter count, thus, improving the network's efficiency and effectiveness, all the while conserving computational resources by eliminating unnecessary parameters [11].

The following are the significances of this project and potential contributions:

Enhanced Breast Cancer Diagnosis Accessibility

Improved Diagnosis Efficiency

Reduced Misdiagnosis Rate

Early detection and Prevention

Conserved Medical Resources and Improved Allocation

Increased Life Saving Rate

Cost-Effective Healthcare Solutions

Promotion of Public Health Awareness

1.4.2Audience

The development of a specialized system for breast cancer diagnosis will bring about significant benefits to various stakeholders.

Medical Professionals: Radiologists and oncologists will benefit from the enhanced accuracy and efficiency of breast cancer diagnosis. The CNN can aid in early detection, reducing the chances of misdiagnosis and allowing for more timely interventions.

Hospitals and Clinics: Healthcare institutions will experience improved workflow and reduced diagnostic errors, which can lead to better patient care and outcomes. It can also streamline the diagnostic process, potentially reducing the burden on healthcare resources.

Breast Cancer Patients: Patients will benefit from faster and more accurate diagnosis, resulting in quicker treatment initiation and improved chances of survival. Additionally, reduced false positives and negatives can alleviate the emotional stress associated with diagnostic uncertainty.

Medical Researchers: Researchers can access a valuable tool for analyzing a vast amount of medical imaging data, facilitating advancements in breast cancer research and treatment methods.

In summary, the proposed depthwise-Inception-ResNet model promises benefits for medical professionals, healthcare institutions, breast cancer patients, and the broader research community by enhancing the accuracy, efficiency, and overall quality of breast cancer diagnosis and care.

2Background Review

Various methods had enhanced breast cancer classification. This section will present works that had been done for breast cancer classification.

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原文内容

Hirra et al.[1] proposed Pa-DBN-BC, a patch-based deep learning method, achieving 86% accuracy in diagnosing cancer from histopathology images. Sahu et al.[6] introduced a model trained on mini-DDSM, yielding 99.17% and 97.75% accuracy for abnormalities and malignancy. Liang and Meng [9] achieved high accuracy in binary and eight-class classification with BreakHis datasets. Alkhaldi et al.[11] utilized ensemble optimization, attaining 92.874% accuracy in Invasive Ductal Carcinoma classification.

Xu et al.[13] introduced an attention mechanism network with 98% accuracy, albeit limited by the smaller BreakHis dataset. Wu et al.[14] trained on 224,426 mammography images, reaching an AUC of 0.895. Chougrad et al.[15] employed transfer learning, achieving 98.94% accuracy post-merging datasets. Yu et al.[16] used SCDA data augmentation with ResNet-50, obtaining 95.74% accuracy,98.55% specificity, and 92.83% sensitivity. Arya and Saha [17] developed a stacked-based ensemble model with 90.2% accuracy for breast cancer prognosis. Whitney et al.[10] highlighted the efficacy of CNN transfer learning in diverse imaging modalities for accurate breast cancer diagnosis.

A summary of the different researchers and their findings and possible results can be found in Table 1

Author Datasets Methods & Models Results

Hirra et al.[1] Histopathology images Patch-based deep learning & Deep belief Network 86%

Sahu et al.[6] Mini-DDSM &

Ultrasound

images(BUSI) AlexNet+ResNet+MobileNeetV2 Abnormalities:99.17% and 97.75% mini-DDSM and BUSI

Malignancy:96.92% and 94.62% mini-DDSM and ultrasound

Liang and Meng [9] BreakHis Convolutional Block Attention Module and Convolutional Multi-Layer Perceptron 95.5%

Alkhaldi et al.[12] Invasive-Ductal-Carcinoma (IDC) Multi-ResNet CNN 92.874%

Xu et al.[13] BreakHis DeNet 98%

Wu et al.[14]224,426 mammography Ensemble of Four ResNets 0.895 in AUC

Chougrad et al.[15] INbreast, DDSM, BCDR VGG16, ResNet50, IncetpionV3 DDSM:97% accuracy,0.98 on AUC;

INbreast:95.5% accuracy,0.97 on AUC

BCDR:96.67% accuracy,0.96 on AUC

Independent database (MIAS):98.23% accuracy,0.99 on AUC

Yu et al.[16] INbreast, mini-DDSM SCDA augmentation

& ResNet-5095.74% accuracy,98.55 specificity,92.83% sensitivity

Arya and Saha [17]1,980 patients’ breast cancer data stacked ensemble model AUC of 0.93 and 90.2% accuracy

Table 1: Summary of Related Works

3Methodology

3.1Approach

The proposed CNN model comprises two individual models with two mechanisms. The basic idea is to combine Inception-V4 Model, Residual Network, and integrate attention mechanism and depthwise convolution which are respectively used to concentrate on relevant features and to reduce the computat ion resources.

3.1.1 Inception Network Version 4(V4)

Inception V4, as shown in figure 1, introduced by Google researchers in 2016, is a deep learning architecture renowned for its advanced techniques, inc luding inception modules that efficiently learn local and global features using filters of varying sizes. It excels in image recognition and offers scalability [18].

Figure 1: Inception V4 Architecture

3.1.2Residual Network

ResNet blocks, as illustrated in Figure 2, were introduced to incorporate residual connections, effectively mitigating gradient-related challenges in deep networks and leading to enhanced training efficiency [19].

Figure 2: Basic ResNet Block

3.1.3Inception-ResNet Block

Figure 3 illustrates the fusion of Inception V4 with ResNet Blocks, creating the Inception-ResNet Blocks structure. This hybrid design incorporates the m ulti-path feature extraction of Inception with the gradient-enhancing properties of ResNet. By combining these elements, Inception-ResNet Blocks enable e fficient learning of intricate features, leading to more accurate and effective deep learning models [19]. The diagram visually showcases the amalgamation o f these techniques, highlighting their collaborative strength in enhancing the network's capabilities.

Figure 3: Inception-ResNet Block & Inception-ResNet Architecture

3.1.4Depthwise Convolution Model

As for depthwise convolution model, it is shown in figure 4 that instead of being an individual model, it is a convolution methodology which reduces the parameters by bypassing unnecessary parameters to deplete the model size and resource being taken [12].

Figure 4: Depthwise Convolution

3.1.5Depthwise-Inception-ResNet Model

Therefore, Depthwise-Inception-ResNet model is constructed by combining all above which shown in figure 5.

Figure 5: Depthwise-Inception-ResNet Network

Networks with attention mechanisms focus on specific areas for more relevant task-related features [20]. Attention combines a reference with keys to c alculate scores, which are then used to determine importance, allowing concentration on specific information. The equations are as follows (equations 1-3).

Attention Score (Q, K)= Q * K^T (Equation 1)

Attention Weights (Q, K)= softmax(Attention Score (Q, K))(Equation 2)

Attention Values (Q, K, V)=Attention Weights(Q, K)* V (Equation 3)

The final network will be integrated with attention, therefore, it is shown in figure 6.

Figure 6: Depthwise-Inception-ResNet-Attention Network

3.2 Technology

The technology this project will be using is displayed in Table 2

Software Framework Tensorflow

Language Python

Libraries Numpy, Keras, Matplolib

Hardware Central processing unit(CPU) Intel(R) Core(TM) i7-8750H CPU @2.2PGHz(12 CPUs),~2.2GHz

Graphic Processing Unit(GPU) NVIDIA GeForce GTX 2060

Table 2: Summary of Relevant Technology involved in this project

3.3 Version management plan

To manage the different versions of codes modification, I plan to use Github as the version management tools for keeping code updated and secure.

URL is as follow: https://github.com/Vio1etV/Deep-Learning-Project.git

4Project Management

4.1Activities

Phase Objectives

Preparation Review breast cancer deep learning.

Identify and narrow issues

Seek possible solutions.

Study classification methods.

Deep learning knowledge absorbing Research breast cancer symptom classification methods

Study at least six CNN models and relevant programming libraries.

Grasp loss functions, optimizers, model building, and optimization.

Investigate extra mechanism for suitability.

Data collection Gather 2-3 datasets from Kaggle

Split them into two classes: benign & malignant

Decide the training and test ratio

Development and Implementation Build Inception-ResNet model.

Add depthwise into Inception-ResNet

Train, analyze, and compare models.

Optimize the chosen model and adjust hyperparameters if needed.

Testing and Finishing up Change other similar datasets to check the generalization capability of the model

Analyze the results and summarize the work

Write Project Report and Prepare presentation

4.2Schedule

The schedule is shown as table 3 below

For instance:1-1 means Phase 1, Objective 1

Table 3: Gantt Chart

4.3Data management plan

.All files including datasets, model codes, references, weekly reports and all sorts will be replicated into three copies for fail safe, one on local computer, one on hard drive, one on github

.Upload the project to github for every modification, synchronize the project on three platforms

Following are documents of the Project for uploading and synchronization:

1.Reports (Weekly, Proposal, Progress, Final)& Presentation PPT

2.CNN model diagram

3.References

4.Datasets Link

5.Model evaluation documents

6.CNN model codes (Different versions)

4.4Deliverables

.The project proposal

.Weekly report

.Progress Report

.Final Project Report

.Project codes

.Project presentation slides

.Project presentation

5 References

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