**Comparative Study of Support Vector Machine and Convolutional Neural Networks model with other in-built image classifiers**

Abstract

One of the best machine learning techniques is Support Vector Machine. If it is combined with the computational power of Convolutional Neural Network, it becomes an immensely powerful classification algorithm. A new model involving Support Vector Machine and Convolutional Neural Network was discovered which gives better accuracy than other image classifiers such as VGG16, RESNET 50, and INCEPTIONV3 models. The dataset used in the study was taken from KAGGLE and consisted of negative breast cancer and positive breast cancer images. The dataset was manually cleaned of unsolicited images and was reduced to a training set of 3538 images belonging to 2 classes and to a testing set of 250 images belonging to 2 classes. It was found that the accuracies of the VGG16, RESNET 50, and INCEPTIONV3 models were 87.64%, 86.09% and 89.35%, respectively whereas the accuracy of the SVM-CNN model was 90.33%.

Introduction

Cancer is a disease in which some somatic cells grow out of control and spread to other parts of the body. Abnormal or damaged cells can grow and proliferate when they do not need to grow. These cells can form tumours, which can be cancerous or non-cancerous. Breast cancer can be defined as abnormal growth of breast cells, most often starting with glandular tissue called the ducts or lobules, or other cells or tissues in the breast. Swelling, skin irritation, and breast lumps can be symptoms of breast cancer. However, many breast cancers have no obvious symptoms. Breast cancer can spread when cancer cells enter the blood and lymph system and are carried to other parts of the body. Breast cancer is the most common type of cancer in women around the world. In 2018, an estimated 266,120 new cases of malignant (invasive breast cancer) are expected to be diagnosed in women in the U.S.A, along with 63,960 new cases of benign (non -invasive breast cancer). As of January 2022, there are more than 3.8 million women with a history of breast cancer in the U.S. This includes women who are currently receiving treatment and women who have completed treatment. Early detection of cancer focuses on identifying the symptomatic patient as soon as possible, so treatment is most likely to be successful. Delayed or inaccessible treatment of cancer reduces the chances of survival, increases treatment-related problems, and increases treatment costs. Pathological images of the breast have become an important tool for early detection of breast cancer. The advantages of image processing are reduced latency for results, improved diagnostic accuracy and efficiency, and reduced costs. Machine learning techniques are used to detect and classify breast cancer images. The main advantage of CNN compared to its competitors is that it automatically detects the key features without any human supervision. There are many algorithms used for classification in machine learning, but SVM is better than most of the other algorithms used as it has a better accuracy in results. The SVM-CNN model also uses less memory because it uses a subset of training points in the decision phase. SVM works well with a clear margin of separation and with high dimensional space. Thus, we aim to prove that SVM-CNN model is a better than the other built-in models like VGG16, RESNET 50, and INCEPTIONV3 models.

**Literature Survey**

Breast cancer is one of the most common malignant tumours and the incidence is rising year after year. The key to reducing breast cancer mortality is early diagnosis and treatment. Currently, mammography is the most widely used method of diagnosing breast cancer. However, due to the large amount of data and negative recording features of early breast cancer, early diagnosis is very difficult. With the advancement of imaging technology and early diagnostic technology, image processing has become an important means of diagnosing early breast cancer [7]. Medical image analysis that combines in-depth study with machine learning demonstrates its elevation in the field of cell division. A new framework based on the robust Convolutional Neural Networks (CNN) -Support Vector Machine (SVM) model was proposed to accurately classify cervical cells. The results showed that a strong feature of the CNN-SVM model could be used in cell division to diagnose cervical cancer early [10]. The most convincing convolutional networks (up to 19 layers of weight) were explored to get the most of image classification. It was demonstrated that representation depth is beneficial to the accuracy of the sections, and that modern functionality in the ImageNet challenge database can be achieved using conventional ConvNet architecture with increased depth [1]. Convolutional networks are at the core of most state-of-the-art computer vision solutions for various use cases such as mobile vision and big-data scenarios. Here we are exploring ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible. [2]. A residual learning framework was introduced to facilitate the training of deeper networks than those previously used. Layers reshape explicitly as residual learning activities in terms of layer input, rather than reading non-reference tasks. Complete proofreading is demonstrated for residual networks that are easy to implement and can obtain precision depths that include a convolutional neural network (CNN) and a straightforward SVM (Vector Support Machine) for image separation [3]. However, CNN used in this study is a simple 2-Convolutional Layer with a Max Pooling model, in contrast to the more complex model [4]. Recent research has shown that CNNs (Convolutional Neural Networks) can produce more accurate results in tasks such as image classification, object recognition, integration, and segmentation in different fields of image processing [5]. Although SVM is a very robust system, achieving such high accuracy is still a mystery. The high accuracy in SVM is due to the lack of a large enough database. When the database is expanded in size, the accuracy of the SVM model decreases. When CNN is used in the database the accuracy of the model increases. It thus proves the growing power of in-depth learning strategies in addition to traditional machine learning strategies [6]. Small-sized images were cropped from high-resolution images, followed by enlargement of the data. Then, in-depth features were extracted from captured images using seven previously trained CNN models (Alex Net, ResNet18, ResNet50, ResNet101, Inceptionv3, DenseNet201, and Inceptionresnetv2). The Support Vector Machines (SVM) category has been used to separate deep features. Classification accuracy obtained separately by various kernel functions such as Linear, Quadratic, Cubic [8]. It was noted that the selection of the feature increases the success of the separation although the number of factors used in the separation decreases [9].

Method

The data images were collected from KAGGLE. The dataset was cleaned by removing images that were unrelated to breast cancer. The SVM-CNN model consists of two convolution layers, three dropout layers, two max pooling layers, and two dense layers. The first convolution layer consists of 32 filters and padding set to same and a RELU activation layer with input layer of 64X64X3. A dropout layer is then added to the model. A max pooling layer is added to the model with pool size as 2 and number of strides as 2. Similarly, another convolution is added to the model. A flattening layer is added to the model followed by a Dense Layer and a Dropout layer. For the output layer, a dense layer is added to the model with a kernel regularizer, and the activation set to linear. The model was compiled with the Adam optimizer and the loss was set to hinge loss and metrics was set to accuracy. The model was fitted with 100 steps per epoch and 10 epochs. The training and testing loss was plotted along with the training and testing accuracy. The model was saved and asked to predict individual cases of negative and positive breast cancer images.

The other image classifiers such as VGG16, RESNET 50, and INCEPTIONV3 models were run on the dataset with 100 steps per epoch and 10 epochs.

The software used were PYTHON and TENSORFLOW. Limitations are that the testing accuracy is at 75% and has further scope to be increased by increasing the number of epochs in the model.

Results and Discussion // Merge Results and Discussion and add headings

It was found that the accuracies of the VGG16, RESNET 50, and INCEPTIONV3 models were 87.64%, 86.09% and 89.35%, respectively whereas the accuracy of the SVM-CNN model was 90.33%.

VGG-16

VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. There are two key drawbacks worth noting if you are working with a VGG network. First, it takes a lot of time to train. Second, the network architecture weights are quite large. Due to its depth and number of fully connected nodes, the trained VGG16 model is over 500MB.

ResNet-50

ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. Although ResNet has proven powerful in many applications, one major drawback is that deeper network usually requires weeks for training, making it infeasible in real-world applications.

Inception v3

Inception v3 is a CNN for assisting in image analysis and object detection and got its start as a module for Google Net. It is the third edition of Google's Inception Convolutional Neural Network, originally introduced during the ImageNet Recognition Challenge. The design of Inceptionv3 was intended to allow deeper networks while also keeping the number of parameters from growing too large. The Inception architecture was designed to perform well even under strict constraints on memory and computational budget. The computational cost of Inception is also much lower than VGGNet or its higher performing successors. This has made it feasible to utilize Inception networks in big-data scenarios where huge amount of data needed to be processed at reasonable cost or scenarios where memory or computational capacity is inherently limited, for example in mobile vision settings. This makes it much harder to adapt it to new use-cases while maintaining its efficiency. This is enabled by the generous use of dimensional reduction and parallel structures of the Inception modules which allows for mitigating the impact of structural changes on nearby components.

SVM-CNN

SVM is chosen because it has a simpler computational process than Deep Learning, so it is easier to apply but with good accuracy. Furthermore, this research also adds a soft-margin objective to the SVM to overcome images that cannot be separated linearly both in the training process and in the implementation stage.

Conclusion

We have done a comparative analysis of the SVM-CNN model with the other built-in methods. It was found that the accuracies of the VGG16, RESNET 50, and INCEPTIONV3 models were 87.64%, 86.09% and 89.35%, respectively whereas the accuracy of the SVM-CNN model was 90.33%. The research is important as it throws light on the innovative approach to predict and classify images of breast cancer and can save lives and reduce cost of diagnosis by avoiding mammography which is a dangerous and inaccurate. The sensitivity of mammography to the index cancer ranges from 63% to 98% and has been reported to be as low as 30% to 48% in dense breasts, hence reducing the accuracy of breast cancer diagnosis by mammography.

This information is provided by [Breastcancer.org](https://www.breastcancer.org/)

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