Early Prediction and Analysis of Fetal Abnormalities Using Deep Learning CNN Models

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Abstract: The purpose of this literature review is to provide a thorough overview of current state-of-the-art approaches, problems, and future possibilities in the field of fetal anomaly classification utilising deep learning CNN Models. The findings from the examination of the 5 influential models will be used to build a robust and accurate deep learning-based system for fetal anomaly classification. This research has the potential to greatly contribute to improved fetal healthcare.

Keywords: Fetal, Anomaly, Classification, Deep Leanring, CNN, Accuracy.

1. INTRODUCTION

Machine learning has a subfield called deep learning, which uses artificial neural networks and algorithms motivated by the brain's structure and function. As opposed to traditional machine learning algorithms, which rely on structured data, deep learning algorithms are designed to work with unstructured data. Deep learning is a type of machine learning in which a model is trained to automatically execute categorization tasks on data such as photos, text, or audio without any human intervention. Neuronal networks, fully connected networks, convolutional networks, and recurrent networks are all examples of deep learning techniques. .

This literature survey aims to provide a formal and comprehensive analysis of ten influential research papers that address the classification of fetal images using deep learning methodologies. By critically examining the existing literature, this survey seeks to identify prevailing trends, highlight challenges, and outline potential directions for future research in this domain. The selected papers encompass a diverse range of topics related to fetal abnormality classification, including deep learning architectures, feature extraction techniques, dataset characteristics, and evaluation metrics. Each paper was reviewed to assess its contribution to the field and extract key insights that can inform the development of an effective deep learning-based system for fetal abnormality classification.

2. LITERATURE REVIEW

The literature review begins with an explanation of the importance of foetal abnormality categorization in prenatal treatment. It emphasises the shortcomings of traditional approaches while emphasising the potential benefits of using deep learning techniques to improve classification accuracy and efficiency[22-28]. Following that, the survey delves into the various deep learning architectures used in the studies, such as convolutional neural networks, recurrent neural networks, and their variants. These architectures are evaluated, giving light on their advantages and disadvantages as well as providing insights into their applicability for foetal image categorization. . The exponential growth of deep learning in recent years is documented by its use in an array of domains. The goal of deep learning, a sub-field of machine learning, is high performance and adaptability. Learn to represent data as a nested hierarchy of concepts within the layers of a neural network, and deep learning will outperform and outflex machine learning R. Chalapathy et al.. When the size of the dataset is larger, deep learning beats more traditional machine learning methods.

3. DIFFERENT TYPES OF CNN MODELS

A subset of Neural Networks known as Convolutional Neural Networks (CNNs) has won several Image Processing and Computer Vision competitions. Exciting areas of use for CNN include image classification and segmentation, object detection, video processing, NLP, and speech recognition. The large amount of feature extraction stages used by Deep CNN to automatically learn representations from data gives it a tremendous learning potential. The various CNN Models will be examined in this section.

1. LeNet
2. AlexNet
3. ResNet
4. GoogleNet
5. VGG

3.1 LeNet:

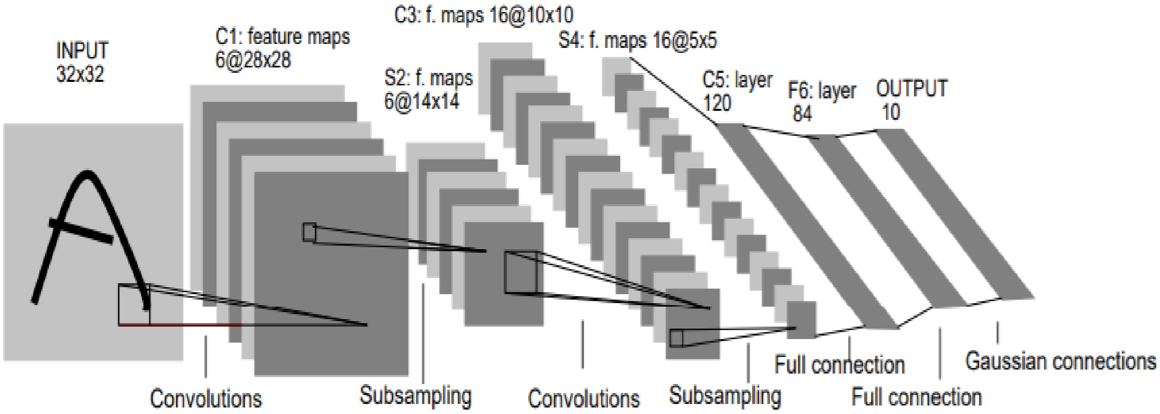

Figure 1. LeNet Architecture

Source (https://iq.opengenus.org/different-types-of-cnn-models/)

The most widely used CNN architecture is LeNet, which was also the first CNN model when it was released in 1998. Initially, the MNIST Dataset's handwritten numbers 0-9 were the focus of LeNet's development. Each of its seven levels can be trained independently of the others. It can take photos that are 32 pixels square, which is far larger than the examples used to train the network. In this case, RELU is the activation function of choice.

3.2 AlexNet:

Alexnet is constructed in 5 conv layers, starting with an 11x11 kernel. Dropout, ReLu activation functions, and max-pooling layers were used for the first time in this design for the three large linear layers. Using the network, we were able to divide photos into a thousand distinct groups. While the network's structure is similar to that of the LeNet, it has many more filters than the original LeNet and is thus better able to classify a wider variety of objects. Furthermore, "dropout" is used instead of regularisation to address overfitting. A simplified view of AlexNet's five convolution and three fully linked layers:

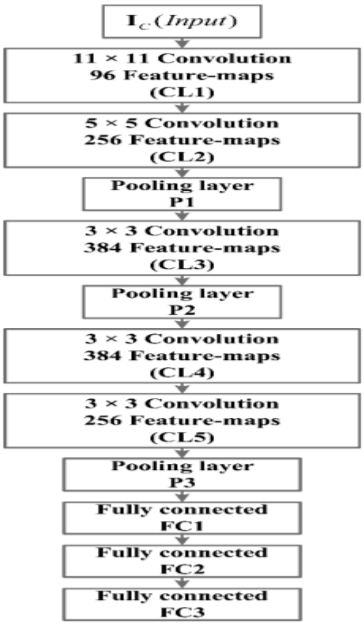

Figure 2. AlexNet Architecture

Source (https://iq.opengenus.org/different-types-of-cnn-models/)

3.3 ResNet:

ResNet is a popular deep learning model developed originally by Shaoqing Ren, Kaiming He, Jian Sun, and Xiangyu Zhang. The article "Deep Residual Learning for Image Recognition" was published in 2015. ResNet is now one of the most popular and successful deep learning models available. ResNets are built from what is called a residual block.

This is built on the idea of "skip-connections" and makes extensive use of batch-normalization to train hundreds of layers without losing speed.

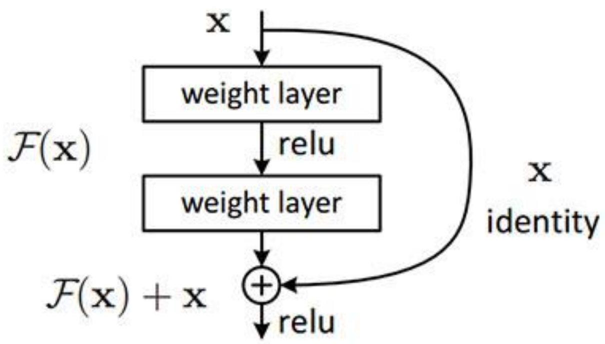

Figure 3. ResNet Architecture

Source (https://iq.opengenus.org/different-types-of-cnn-models/)

The first thing that jumps out at us from the aforementioned graphic is the existence of a direct connection that bypasses multiple stages of the model. The foundation of residual blocks is the'skip connection,' as it is commonly called. The output is not consistent due to the skip connection. The input 'X is multiplied by the weights of the layer, and a bias term is added, if the skip connection is not present. The architecture takes its cue from VGG-19, which influenced its 34-layer plain network and the addition of shortcut and skip connections. These residual blocks and skip connections transform the original design into a residual network, as seen in the schematic below.

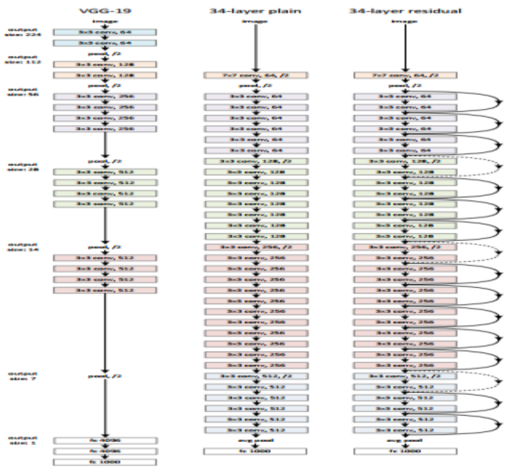

Figure 4. VGG-19 Architecture

Source (https://iq.opengenus.org/different-types-of-cnn-models/)

3.4 GoogleNet / Inception:

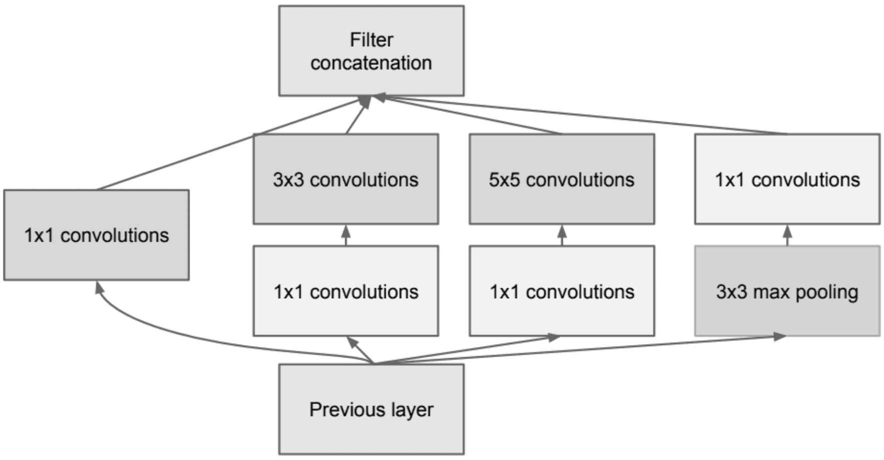

Figure 5. GoogleNet Architecture

Source (https://iq.opengenus.org/different-types-of-cnn-models/)

According to the results of the ILSVRC 2014 competition, GoogleNet (or Inception Network, depending on who you ask) came out on top thanks to its error rate in the top five systems of 6.67 percent. This model is a refinement of prior work by Google on a notion called LeNet. This concept was inspired by the movie "Inception." Similar to the 22-layer GoogLeNet, the Inception Network is a deep convolutional neural network. These days, you can use GoogLeNet for all sorts of computer vision tasks, such facial recognition, adversarial training, and more. Here is how the Inception Module appears:

3.5 VGG:

The VGG convolutional neural network architecture has been in use for quite some time. Research on how to increase the density of such networks served as the basis for this. The network employs relatively compact 3-by-3-cell filters. The network is otherwise characterised by its simplicity, with components including a completely linked layer and a simple pooling layer.

VGG was built with 19 layers, the same as AlexNet and ZfNet, to preserve the positive association between network depth and representational efficacy.

One of the top networks from the 2013 ILSVRC competition, ZfNet, claims that utilising smaller filters can boost CNNs' efficiency. In light of these results, VGG switched out the 11x11 and 5x5 filters for a stack of 3x3 filters, proving that a combination of smaller filters (here, 3x3) can achieve the same outcome as a larger filter (here, 5x5 or 7x7). Using modest filter sizes has the additional benefit of lowering the number of parameters, which in turn simplifies the computation. These results have motivated a new line of investigation at CNN, which is centred on using increasingly finer filters.

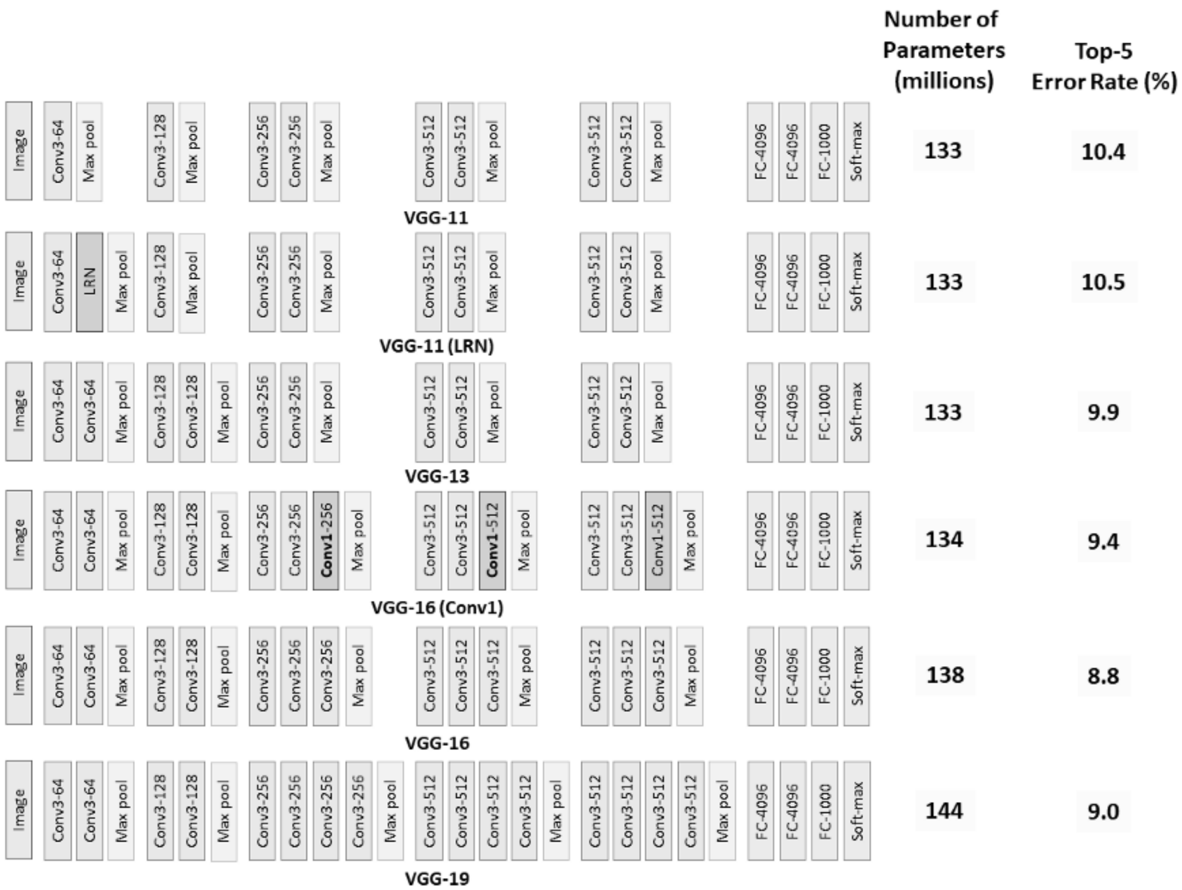

Figure 6. VGG Architecture

Source (https://iq.opengenus.org/different-types-of-cnn-models/)

4. CONCLUSION

The goal of this literature review is to offer readers with a comprehensive summary of the present state-of-the-art methods, challenges, and potential applications of deep learning CNN models in the field of foetal abnormality classification. The results of this analysis of the 5 most important CNN Models will be used to develop a deep learning-based system that is both reliable and accurate for identifying foetal anomalies prediction. The advancement of prenatal care stands to benefit tremendously from the findings of this research work.

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