



DETECTION OF THYROID STAGES CLASSIFICATION BY USING CONVOLUTION NEURAL NETWORK TECHNIQUES

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ABSTRACT:

Thyroid disorders are prevalent endocrine diseases affecting millions of people worldwide. The accurate and timely classification of thyroid stages is crucial for effective diagnosis and treatment. In recent years, convolutional neural networks (CNNs) have emerged as a powerful tool for image recognition and classification tasks. The proposed methodology involves a multi-step process. First, a comprehensive dataset of thyroid images representing different stages is compiled and pre-processed for training and validation purposes. Next, a CNN architecture is designed, comprising multiple layers of convolutions, pooling, and fully connected layers. The model leverages the capability of CNNs to automatically learn and extract relevant features from the input images, making it well-suited for medical image analysis tasks. The training of the CNN is conducted using a large-scale dataset to optimize its performance and generalization ability. The model is fine-tuned through an iterative process to achieve the highest possible accuracy and precision for thyroid stage classification.

INTRODUCTION:

Thyroid disorders are prevalent medical conditions affecting millions of people worldwide. The thyroid gland plays a crucial role in regulating various bodily functions, including metabolism, energy production, and temperature control. When the thyroid gland malfunctions, it can lead to various health issues, such as hyperthyroidism (overactive thyroid) or hypothyroidism (underactive thyroid). Detecting and classifying the stages of thyroid disorders is essential for effective medical diagnosis and treatment.

Traditional methods for diagnosing thyroid disorders involve blood tests, physical examinations, and ultrasound imaging. While these methods have been valuable, they may not always provide accurate and timely results. Moreover, the interpretation of test results can be subject to human error and variations among medical professionals.

EXISTING SYSTEM:

A growing number of studies show that the human microbiome plays a vital role in human health and can be a crucial factor in predicting certain human diseases. However, microbiome data are often characterized by the limited samples and high-dimensional features, which pose a great challenge for machine learning methods. Therefore, this paper proposes a novel ensemble deep learning disease prediction method that combines unsupervised and supervised learning paradigms. First, unsupervised deep learning methods are used to learn the potential representation of the sample. Afterwards, the disease scoring strategy is developed based on the deep representations as the informative features for ensemble analysis. To ensure the optimal ensemble, a score selection mechanism is constructed, and performance boosting features are engaged with the original sample. Finally, the composite features are trained with gradient boosting classifier for health status decision. For case study, the ensemble deep learning flowchart has been demonstrated on six public datasets extracted from the human microbiome profiling. The results show that compared with the existing algorithms, our framework achieves better performance on disease prediction.

DISADVANTAGE:

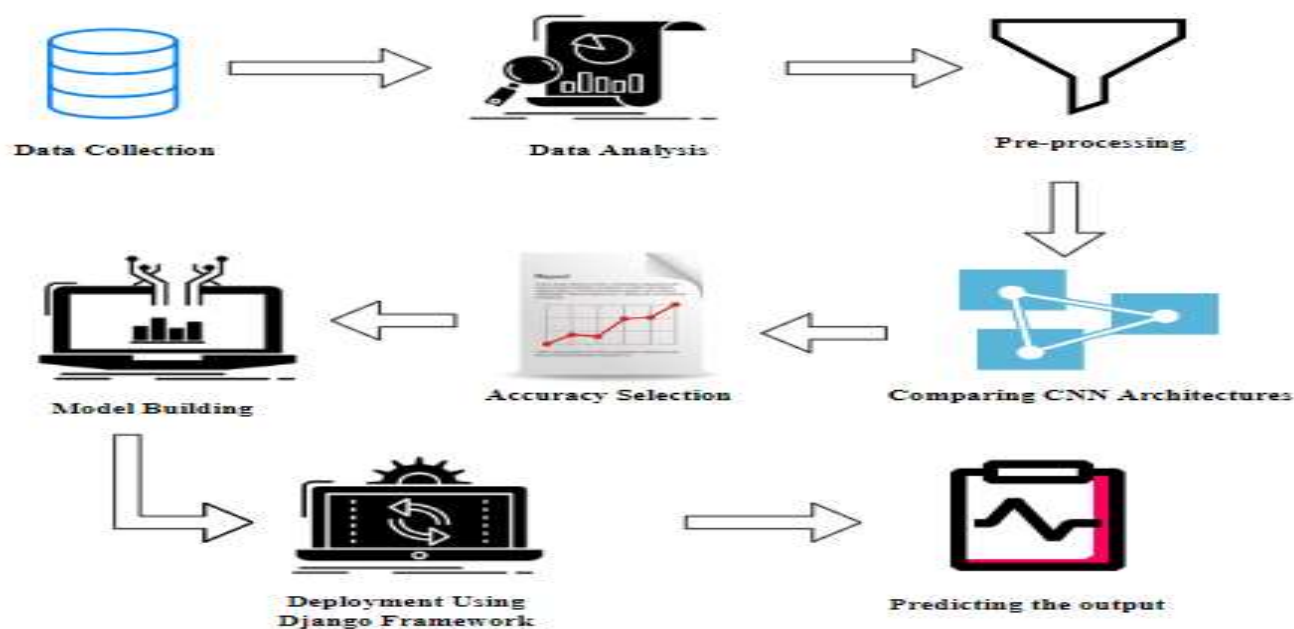
- They did not implement the deployment process.
- They didn't specific disease particularly. Because different disease caused by different factors.
- They did not do image preprocessing process.
- They are using sequential learning approach

PROPOSED SYSTEM:

We proposed a system to develop the project using Deep learning algorithm. Recently, Deep learning and Artificial intelligence has played a big role in various industries for their improvement and development. So, we tried to implement Deep learning algorithm to diagnosis the thyroid. We collected the previous record of patient who had the thyroid and who doesn't have the disease and those who had symptoms. By collection those people's information our machine is tried to identifies the pattern of the datasets by various performing calculations. After identifies the pattern in image using various deep learning algorithm the model can able to predict the instance based on previous information's. If you image related to his has given to input then the algorithm can tell whether it is affected or not.

ADVANTAGE:

- We deploy production level application.
- Accuracy and performance measurements are improved.
- We specifically classify 4 disease stages.
- We compared more than a two architecture to getting better accuracy level.

SYSTEM ARCHITECTURE:**LIST OF MODULES:**

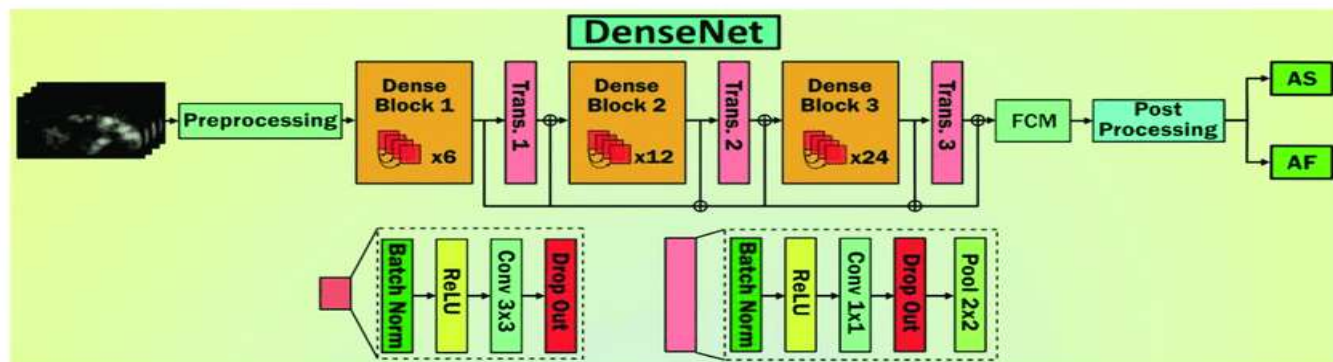
- DENCE NET
- LENET

DENCE NET:

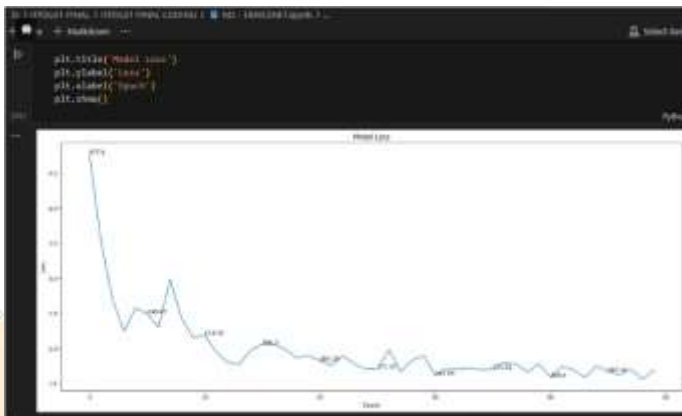
Dense Connectivity: DenseNet introduces dense connections between layers, where each layer is connected to all preceding and subsequent layers in a feed-forward manner. This means that the feature maps from all previous layers are concatenated and fed as inputs to the current layer. This dense connectivity creates a very deep network, which improves feature reuse and information flow through the network.

Growth Rate: DenseNet controls the number of feature maps learned in each layer through a parameter called the growth rate. The growth rate determines how many new feature maps are added to each layer concerning the number of input feature maps. It acts as a form of bottleneck, allowing the network to stay more compact and efficient.

Transition Layers: In DenseNet, transition layers are used to control the spatial dimensions and reduce the number of feature maps before feeding them into the next dense block. These transition layers typically consist of a batch normalization layer, a 1x1 convolutional layer, and an average pooling layer. The average pooling layer reduces the spatial dimensions, while the 1x1 convolutional layer reduces the number of feature maps, thereby compressing the information.



RESULT:



LENET:

The LeNet architecture is a pioneering convolutional neural network (CNN) architecture developed by Yann LeCun and his colleagues in the early 1990s. It played a crucial role in the advancement of deep learning and was specifically designed for handwritten digit recognition tasks, such as recognizing digits in checks and postal addresses. LeNet laid the foundation for modern CNNs and their applications in image recognition and computer vision tasks.

The LeNet architecture consists of the following layers:

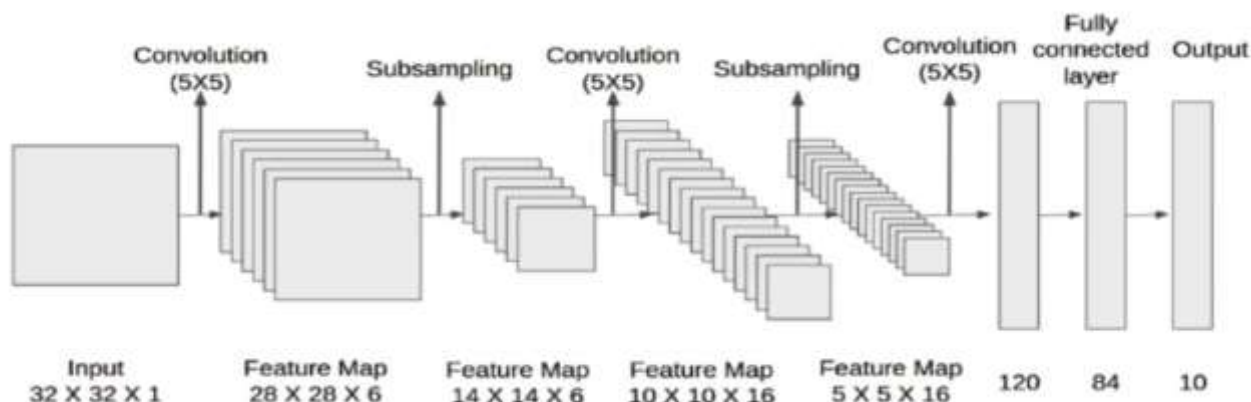
Input Layer: This layer accepts the input image, which is typically a grayscale image of a handwritten digit. The input images are usually of size 32x32 pixels.

Convolutional Layers: LeNet uses two convolutional layers to extract features from the input images. Each convolutional layer applies convolutional filters (also called kernels) to the input image, capturing different patterns and features. These filters slide over the image to create feature maps.

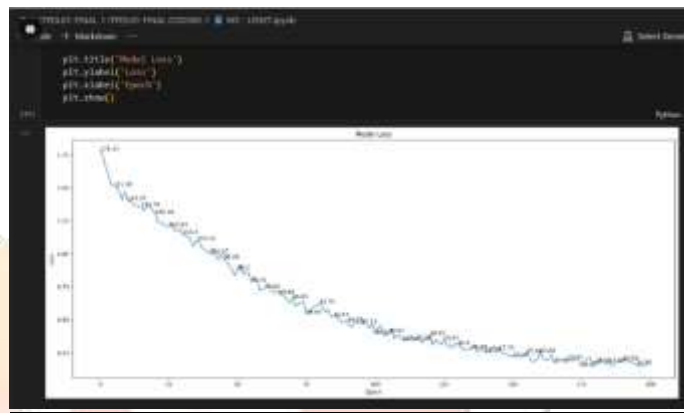
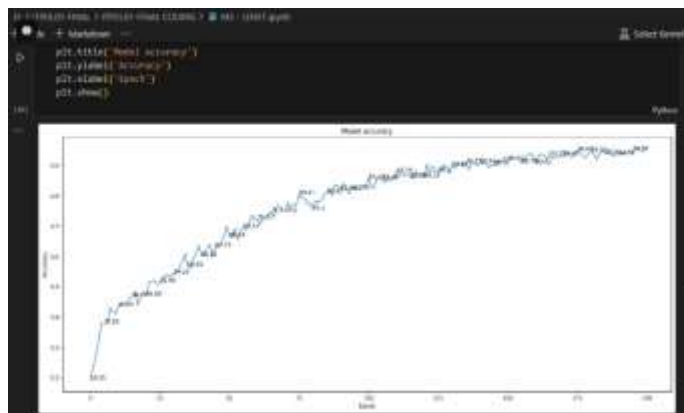
Subsampling (Pooling) Layers: After each convolutional layer, a subsampling layer (also known as a pooling layer) is applied to reduce the spatial dimensions of the feature maps and help in retaining important information while reducing computation.

Fully Connected Layers: The subsampled feature maps are then flattened and passed through fully connected layers, which are traditional neural network layers. These layers are responsible for making classification decisions based on the extracted features.

Output Layer: The final fully connected layer produces the output of the network, which represents the predicted class probabilities. For handwritten digit recognition, this would typically involve 10 output nodes, each corresponding to a digit class (0 to 9).



RESULT:



FUTURE WORK:

Future work would involve more optimization on hyperparameters and model aspects such as which layers to freeze versus make trainable during transfer learning. Due to computing resource and time constraints, most model implementation decisions were made by examining the convergence of the model and relative metrics from training versus validation, but an exhaustive hyper parameter search would have been a more empirical approach.

CONCLUSION:

In conclusion, our research project represents a significant step forward in the field of thyroid disorder diagnosis. By successfully developing and implementing a Convolutional Neural Network-based system, we have unlocked the potential for accurate, efficient, and ethical thyroid stage classification. This work not only benefits healthcare professionals but also holds promise for improving the lives of individuals affected by thyroid disorders. As we move forward, we remain committed to ongoing collaboration, refinement, and further advancements in this critical area of medical technology.

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