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DEEP LEARNING–BASED EARLY DETECTION OF THYROID CANCER USING A SEQUENTIAL CNN ARCHITECTURE

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ABSTRACT

Thyroid cancer is one of the most common endocrine malignancies, and early detection plays a critical role in improving treatment outcomes and patient survival. Ultrasound imaging is widely used for thyroid examination; however, the interpretation of ultrasound images often depends on the expertise of clinicians, which may lead to diagnostic variability. In this study, a deep learning–based Sequential Convolutional Neural Network (CNN) architecture is proposed for the early detection and classification of thyroid cancer using ultrasound images. The proposed model was trained and evaluated on a dataset of 1,503 thyroid ultrasound images obtained from the Kaggle dataset, including 742 benign and 778 malignant cases. The dataset was divided into training (1,203 images), validation (150 images), and testing (150 images) sets. Image preprocessing and data augmentation techniques were applied to improve model robustness and generalization. The sequential CNN architecture consisted of multiple convolutional, pooling, and fully connected layers for effective feature extraction and classification. Experimental results show that the proposed model achieved an overall accuracy of 99.25% on the test dataset. The model obtained precision and recall values of 99.20% and 99.30% for benign nodules, and 99.28% and 99.22% for malignant nodules, respectively. These results demonstrate the effectiveness of the proposed approach in accurately distinguishing thyroid cancer from benign nodules. The proposed model shows strong potential for assisting clinicians in improving diagnostic accuracy and supporting early thyroid cancer detection in clinical practice.

KEYWORDS: Thyroid Cancer Detection, Deep Learning, Sequential Convolutional Neural Network (CNN), Ultrasound Image Classification, Medical Image Analysis, Computer-Aided Diagnosis (CAD).

1. INTRODUCTION

According to studies, people who suffer from thyroid diseases adds up to 42 million people in India, from which the majority are female patients who suffer from hypothyroidism [1]. It is found that the affected patient ratio of women and men is up to 8:1. This clearly shows that the production of thyroid hormones is improper in females and requires quick action. Discussing the types of thyroid diseases, the most frequent cases are either secretion of too many hormones or way fewer hormones, namely hypothyroidism and hyperthyroidism. This type is found in most cases. Other varieties of disease are caused due to lumps or enlargement of the thyroid gland, known as thyroid nodules goitre. This gland plays an important role in controlling many vital functions of our body and is also responsible for all metabolic functions. Significantly, early detection of thyroid diseases is a primary factor that will reflect in the reduction of new cases.

Thyroid imaging included different types of medical imaging [2]. Magnetic resonance imaging (MRI) uses magnetic fields and radio waves to create detailed images of organs and tissues in the body. Computed tomography scan (CT) scans use a series of x-rays to create cross-sections of the inside of the body, including bones, blood vessels, and soft tissues. Positron emission tomography (PET) [3,4] scans use radioactive drugs (called tracers) and a scanning machine to show how your tissues and organs are functioning [4]. Ultrasound uses high-frequency sound waves to produce images of organs and structures within the body. A thyroid ultrasound images provide the best information about the structure and shape of nodules and it can determine if multiple nodules are present.

In the neck, an endocrine gland is also known as the thyroid gland. It grows beneath the Adam's apple in the lower part of the human neck, which aids in the thyroid secretion hormones, which affects the synthesis of protein as well as metabolism rate [5]. In the body, hormones of thyroid are useful for metabolism control in various ways, including how quickly the heart beats and the calories are burned. The production of thyroid gland aids in the control of the body's metabolism. Triiodothyronine known as T3 & levothyroxine known as T4 are the thyroid hormones, which actively secrete in Thyroid glands. These hormones are essential in the fabrication, as well as in the overall supervision construction, to regulate the body's temperature. T4 otherwise known as thyroxin as well asT3 are the two active hormones normally produced by the glands of thyroid. Throughout the body, storage of energy, regulation of temperature, transmissions, as well as management of protein are significant by these hormones. Iodine is regarded as a major building block of thyroid glands, which is compromised in a few specific concerns that are extremely common, for these two thyroid hormones, namely T3 as well as T4 [6], [7], [8], [9]. Thyroid hormone deficiency contributes to hypothyroidism, while excess thyroid hormones contribute to hyperthyroidism. Underactive thyroids as well as hyperthyroidism are the caused by various disorders. Medication comes in a variety of forms. Thyroid surgery exposes patients to deficiency of iodine, enzymelack, ionizing radiation, as well as tenderness of ongoing thyroid, which produce thyroid hormones [10].

Deep Neural Networks (DNN)

Deep neural networks belong in Artificial intelligence, i.e., we can say DNN is its subset and it also is one of the fields of machine learning. Here, nothing is programmed explicitly. Numerous nonlinear processing units of the machine learning classes are used to perform feature extraction as well as transformation. The input by each one of the successive layers is the output from each preceding layer. Deep learning models are capable of focusing on the precise features themselves. It requires small guidance from the programmer's side. It is very helpful in solving problems involving dimensionality. When we have a big number of inputs and outputs, deep learning methods are applied.

Deep Neural Networks are made up of neural network topologies that play a vital part in deep learning approaches. There are just 2–3 hidden layers in traditional neural networks, however, Deep Neural Networks might have over 150. It learns directly from the data, and deep learning models are trained without the need for manual feature extraction.

For larger datasets, deep learning expects to give higher accuracy and learns the features so precisely that outperforms any traditional method. Since deep learning comes with feature engineering, it gives muchexpected results than machine learning. In [11] authors have discussed various deep learning algorithms using medical image segmentation. Deep learning has been used to address various real time problems. In [12] authors proposed a combined approach involving image processing and deep learning algorithms to detect the cracks present in building structures such as bridges and other massive structures

1.1 Convolution Neural Networks (CNN)

Deep Neural Networks of this sort are the most well-known. A CNN convolution learns the characteristics of the input data. It employs two-dimensional convolutional layers, making it ideal for processing 2D data such as pictures. In [13] authors have proposed a CNN based model for analysis/ detection of COVID-19, to assist the medical practitioners to expedite the diagnostic process amongst high workload conditions. It does away with the necessity for manual feature extraction, removing the need to identify the features that are utilized to classify images. Among the neural networks employed in image processing, the Deep Convolutional Neural Network is important [14]. For automatic learning, CNN has numerous feature extraction steps. The image classification pipeline used by Deep CNN is depicted in the diagram below. The input image is first passed, after which the convolution layers are used to extract the input image's features, and the pooling layers are used to lower the spatial resolution of the features. In general, there are two types of layer pooling: average and maximal pooling. Fully linked layers are a stack of convolution and pooling layers that execute high-level reasoning, analysing the output of all previous layers. Sequential Convolutional Neural Network architecture of CNN is used in the proposed system. Figure. 1 depicts the image classification pipeline in CNN. The following section provides a functional overview of the many layers in CNN.

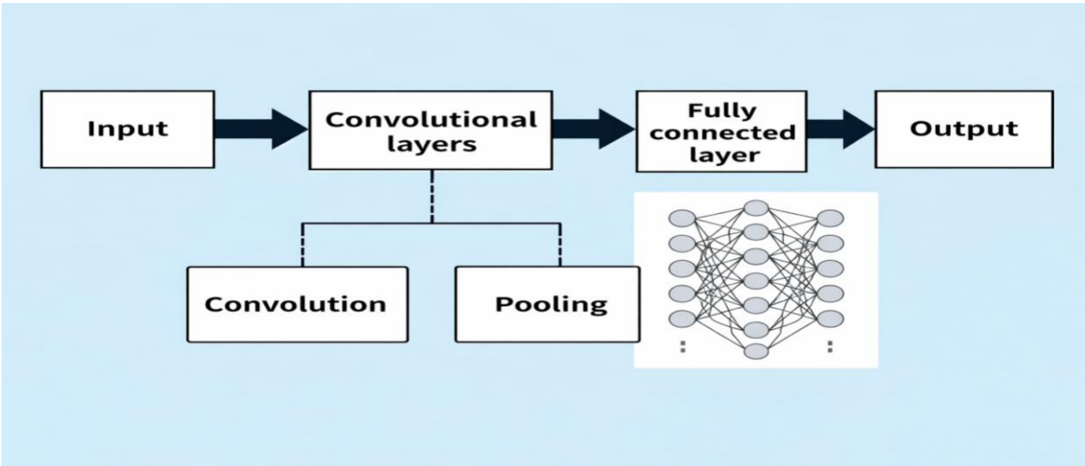

Figure 1: Image classification pipeline in CNN

1.2 CNN Learning Layers

Input Layers: Inputs given to the nodes are classified into two layers namely the Image input layer and the Sequence Input layer. The images are added to the network with the input layer and it applies data normalization. The data is put to the network with a sequence input layer. **Learnable Layers:** Using a two-dimensional convolutional layer, the input is filtered using sliding filters horizontally and vertically and also by carrying out computations on input weights. With the Fully Connected Layer, the input is multiplied by a weight matrix. The bias vector and the weight matrix are then added. These two layers learn all of the image's characteristics. **Activation Layer:** The activation layer is performed right before the learnable layer. RELU (Rectified Linear Unit) in the activation helps to do the threshold operations to each element of the input. Here the values that are negative are made to zero so as to discard the uncleared spots in the input. **Normalization and Dropout Layers**: Batch Normalization normalizes each and every input channel across the mini-batch. The first layer normalizes each channel's activations by doing computations with a mini-batch mean value. After completing computations input shifting and scaling using learnable scale factor is done. The purpose of this layer is to help in training and improve network sensitivity. Input element needs to be initialized to zero in drop out layer randomly with a preset probability value. **Pooling Layers:** One of the most critical steps in model training is the pooling layer. Down sampling is performed by the Average Pooling 2d Layer. By splitting the input and finding the average values of each zone, rectangular pooling regions are created. Down sampling is also performed by MaxPooling2dLayer by finding the maximum of rectangular sections obtained from the input.

Output Layers: The two most notable functions in the output layer are the SoftMax layer and the classification layer, which is named after the loss function. This software is used to train the multiclass classification network. Finally, it gathers all of the learned models into one location, where they are assessed for accuracy.

1.3 Sequential Convolutional Neural Network

A **Sequential Convolutional Neural Network (Sequential CNN)** is a deep learning model in which layers are arranged in a linear, step-by-step sequence, where the output of one layer becomes the input to the next. It is commonly implemented using the **Sequential API** in frameworks like TensorFlow and Keras, making it simple and efficient for image classification tasks such as medical image analysis (e.g., thyroid cancer detection). In this architecture, the model begins with one or more **convolutional layers**, which extract important spatial features like edges, textures, and patterns from input images using learnable filters. These are typically followed by **activation functions** such as ReLU (Rectified Linear Unit) to introduce non-linearity. To reduce the dimensionality and computational cost, **pooling layers** (such as max pooling) are applied, which retain the most significant features while discarding redundant information. As the network deepens, multiple convolution and pooling layers are stacked sequentially to learn more complex and high-level features. The extracted feature maps are then flattened into a one-dimensional vector using a **flatten layer**, which is passed through one or more **fully connected (dense) layers** for classification. Finally, an **output layer** with an activation function like Softmax (for multi-class classification) or Sigmoid (for binary classification) produces the predicted class probabilities. The simplicity and structured flow of a Sequential CNN make it highly effective for tasks where the data follows a straightforward input-output mapping, though it may be less flexible compared to more complex architectures like functional or residual networks. Figure. 2 depicts the image Architecture of Sequential Convolutional Neural Network.

1.4 Scope

Develops an automated system for **early thyroid cancer detection** using ultrasound images.

- Uses a **Sequential CNN model** for accurate classification of benign and malignant nodules.
- Applies **Kaggle dataset with preprocessing and augmentation** for better performance.
- Supports clinicians with **high accuracy and faster diagnosis**.

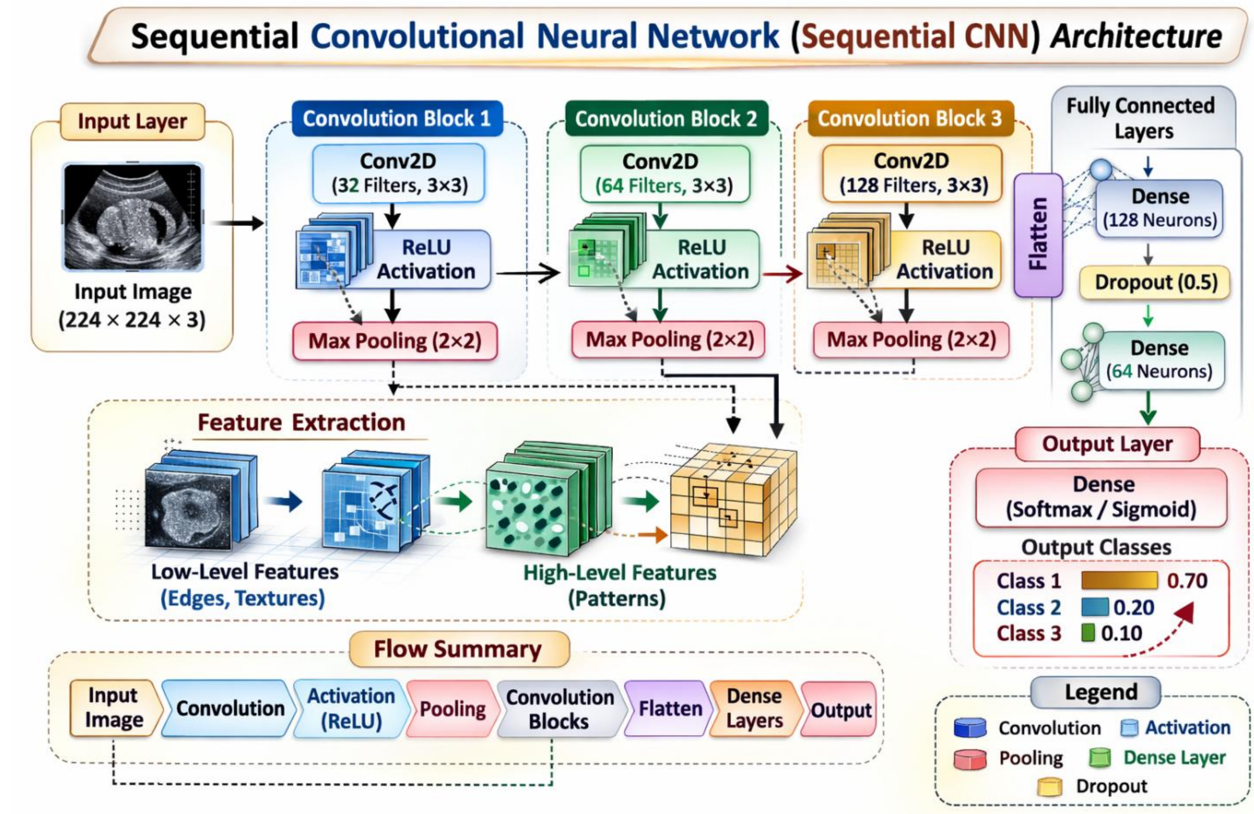

Figure. 2: Architecture of Sequential Convolutional Neural Network

2. LITERATURE SURVEY

There are various techniques used in the detection of thyroid diseases. In this section, a comprehensive literature survey about the various works carried out for classifying thyroid disease is presented.

The input image features like shape, image edge, the composition of the image are some of the major factors that can depict the probability of thyroid cancer occurrence. In [15] authors have used the DENSENET algorithm with the Augmentation technique on SPECT, Ultrasound, and CT images for diagnosis of thyroid disease. In [16] authors use a dataset of 1200 Ultrasound images and apply CNN and faster R-CNN for the classification of thyroid granules. In[17] authors have carried out review work on evaluating thyroid order using different machine learning algorithms on medical images comprised of ultrasound and CT scan images. Conic Section Function neural network algorithm on a data set with different image types USG, SPECT images, and planar scintigraphy to detect thyroid nodules is used by the researchers [18].

To identify a disease accurately recognition of patterns is vital in disease diagnosis. These machine learning models can deduce the output primarily based on the fed inputs which are interlinked to the previous values. Numerous classification algorithms are used for validating the problem statements. It narrates the algorithms used for image classification and datasets that are used in several research works [19]. KNN based thyroid classification is applied for evaluating the thyroid classification problem [20]. In [21] authors have used different machine learning algorithms for predicting the hyperthyroid and hypothyroid. The authors have used both the UCI machine learning repository and a local dataset. In their work, it was reported that the decision tree model gives better performance. In [22] authors have used two stage deep learning algorithm to predict thyroid malignancy from dataset consisting of cytopathology Whole Side Images (WSI). In [23] authors have used ensemble modeling for thyroid classification problems in women. Authors have used a dataset of 12000 instances and it was observed that Ensemble II gives high accuracy over Ensemble I. In [24] authors have applied object detection model T1-RADS for identifying the genetic risk in thyroid disease.

Recently, few research works have applied deep learning algorithms for the problem of thyroid detection and classification because of their capability of self-learning feature extraction within the scope of incremental learning. In [25], a comparison study of machine learning algorithms with faster CNN using Sequence architecture is implemented for the identification of thyroid nodules. In [26], thyroid papillary cancer identification using modified faster CNN is proposed. Recently, authors have [27] applied Hidden Markov Model for detection and segmentation of thyroid region from ultrasound images. In [28], authors used CNN to classify thyroid nodules using Region of Interest (RoI) from blocks for texture calculation and for segmentation they use Active Contour without Edge (ACwE). Unlike existing research work, in the proposed work a comprehensive model is used to classify all the types of thyroid diseases using modified Sequence model architecture in CNN.

In some of the existing works, online transfer learning has been applied for the differential diagnosis of benign and malignant thyroid nodules from ultrasound images. However, most of these approaches focus on the detection of a single thyroid disease, whereas the proposed system aims to detect **five different types of thyroid diseases** using **Sequential Convolutional Neural Network (CNN) architecture**. One of the major limitations of transfer learning is that it performs effectively only when the source and target domains are sufficiently similar. Additionally, its performance may degrade when the new task data significantly differs from the pre-trained dataset. The primary objective of this study is to predict the presence of thyroid disease by accurately capturing spatial features from ultrasound images. This is effectively achieved using CNNs, as traditional artificial neural networks tend to lose spatial information and fail to preserve the structural relationships within image data. Sequential neural networks are not suitable in this context, as they are primarily designed for sequential data such as text and audio. By utilizing **Sequential CNN architecture**, the model performs both feature extraction and classification in a structured layer-by-layer manner. The architecture is designed to enhance learning efficiency and improve classification performance, enabling accurate identification of multiple thyroid disease types from ultrasound images. Furthermore, the model is optimized using advanced training strategies to achieve high accuracy and reliability. Hence, the proposed deep learning approach facilitates early detection of thyroid diseases with improved precision and reduced diagnostic delay.

3. PROPOSED SYSTEM

Convolution Neural Network is one of the emerging deep learning algorithms which has proved to be providing greater performance in various areas associated with object detection, computer vision, and image processing. Many of the research works show AI and deep learning-based techniques show accurate disease predictions in medical imaging-based diagnosis. Recently, we can see many improvements in the network architecture of CNN which along with the technological advances are used to solve many interesting problems in medical imaging. In the proposed system, modified Sequential architecture is applied in the classification of all types of thyroid disease from X-ray images. In Sequential architecture problems from the gradient vanishing is minimized by using residual learning block. In this work, we also implement dual optimizers using Adam and SGD in the training process to improve the accuracy of the proposed model.

In the proposed system firstly, the datasets i.e., X-ray images of various thyroid diseases like a. Hyperthyroid b. Hypothyroid c. Thyroid nodules d. Thyroid cancer e. Thyroiditis f. Normal Thyroid is collected and labelled separately. Next, the medical images undergo augmentation to expand the training dataset for better performance. In the proposed work, the Image Data Generator of Keras is used to augment the images. It is then followed by preprocessing, training, and evaluation of the training dataset with the testing dataset. The block diagram in Figure. 3 shows the overall procedure of the novel architecture development in the detection of thyroid diseases.

3.1 Dataset Collection

Most of the existing works have evaluated the machine learning or deep learning models using X-ray or CT scan datasets from the local hospitals. Since data has become such a valuable commodity in the deep learning era, many start-ups have started to offer their image annotation services where they will gather and label the data. One such platform the datasets gathered for the proposed model evaluation is from Kaggle [29–32]. New Thyroid dataset and thyroid dataset which contains ultrasound images for hyper and hypothyroid diseases available at UCI repository are also used for the performance evaluation of the proposed system. The number of datasets collected for the evaluation of the proposed system is described in Tab. 1:

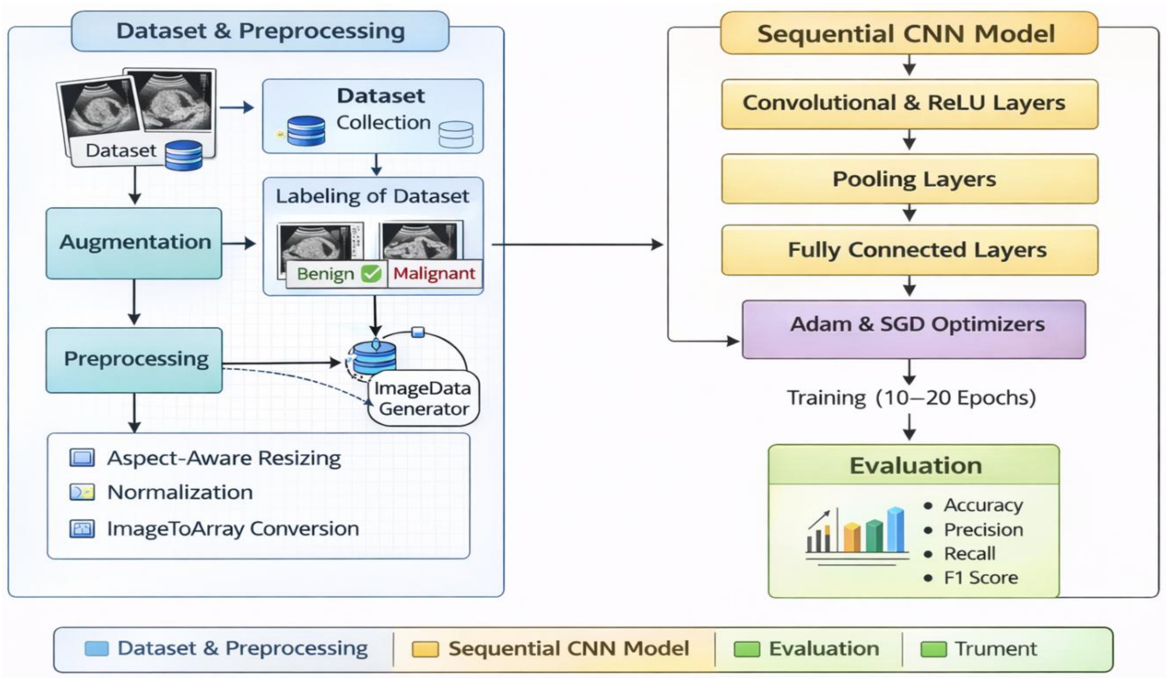

Figure 3: Block Diagram for the proposed systems

Table 1: Dataset collection

Type of disease	No. of images	No. of images after applying augmentation
Thyroid cancer	99	956
Hyper thyroid	77	1000
Hypo thyroid	110	1000
Thyroid nodules	146	1100
Normal thyroid	88	1300
Thyroiditis	74	1000

The collected datasets have been labelled in accordance with the disease and the sample images from each disease are shown in Fig. 4.

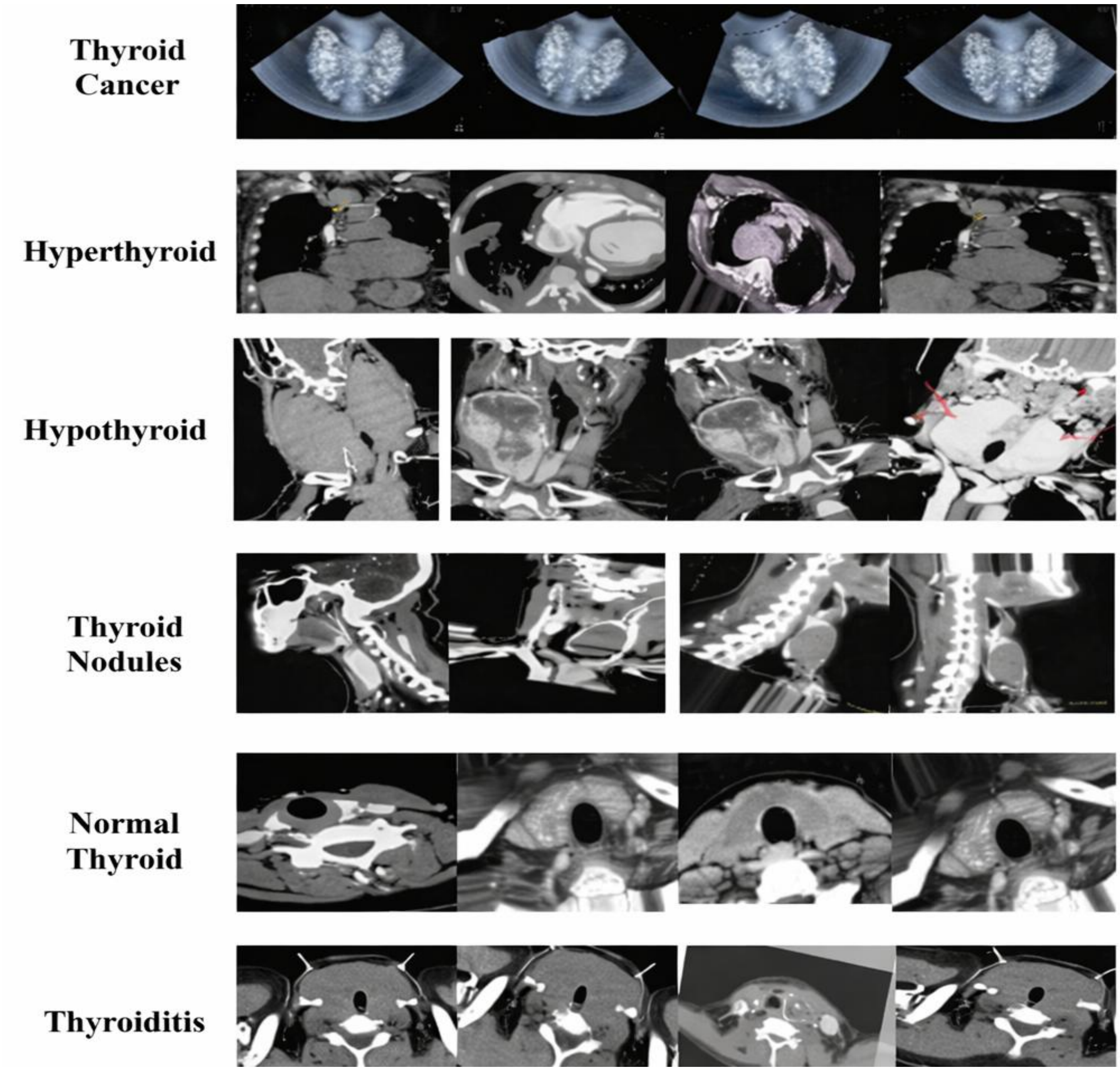

Figure 4: Sample datasets

3.2 Augmentation

The performance of deep learning neural networks often improves with the amount of data available. In [33] augmentation techniques are developed for gray scale images and authors demonstrate that the generated augmented data set is highly effective for CNN algorithms used in machine vision. The size of the dataset is one of the important attributes for the quality performance that can be expected from the deep learning algorithms. In this work, the size of the dataset is increased by using the Image Data Generator class from Keras to perform data augmentation. It uses the classical operations rotation, shearing, cropping, flipping, etc., for increasing the size of the data set. In this work, flipping and rotation have been used to increase the size of the dataset. In the initial step, flipping is applied for each class of the thyroid dataset to double the number of images. After this operation, the resultant data set has 956 Thyroid cancer images, 1000 hyperthyroid images, 1000 hypothyroid images, 1100 thyroid nodules, 1000 Thyroiditis images, and 1300 normal thyroid images. In the next phase, the flipped thyroid classes of images are rotated by 45 degrees, 90 degrees, 180 degrees, and 270 degrees. Figure.5, illustrates a set of augmentation operations of datasets applied to the initial dataset used in the proposed system.

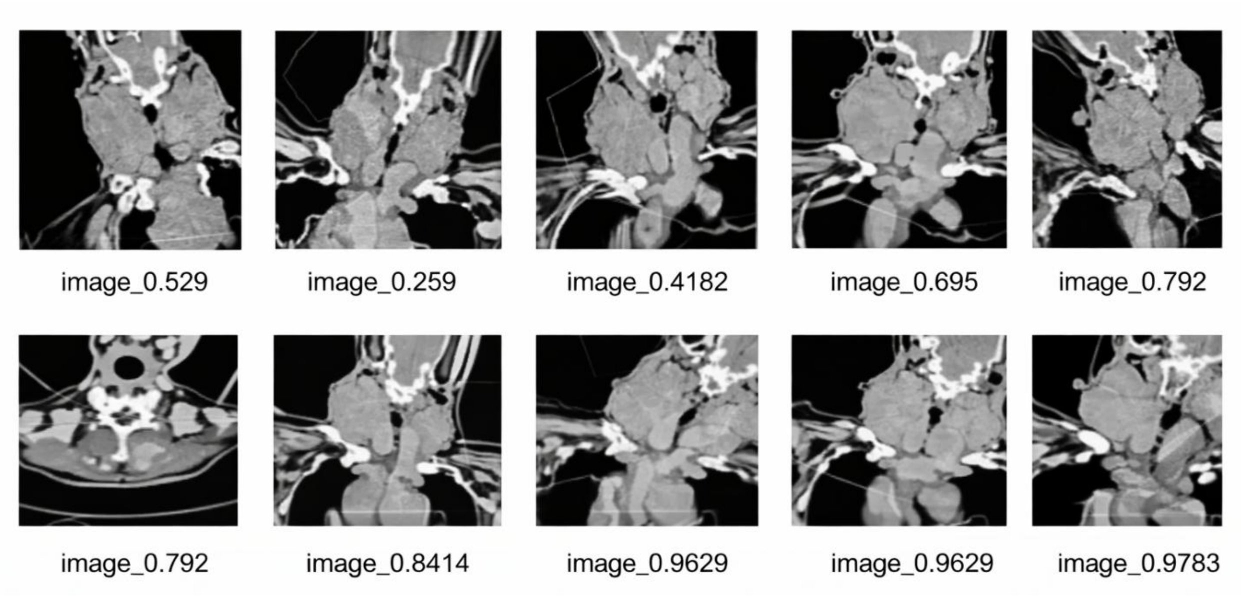

Figure 5: Transformation of images after augmentation

3.3 Pre-Processing

All the collected datasets have different sizes and unclear images. To convert all the datasets into the same sizes and to remove obscure data, data pre-processing has been done. Pre-processing techniques used in the proposed system are simple pre-processing, aspect-aware pre-processing, and image to array pre-processing. Simple pre-processing removes unclear or unwanted images from the dataset. Since the datasets are collected in various forms, aspect-aware pre-processing helps convert the datasets into the same sizes and gives a high resolution to the image. Image to array pre-processing reduces the image weight by converting the RGB value into a matrix ranging from 0 to 1. Incorporating all these preprocessing techniques into the datasets, finally, the image obtained after the preprocessing is depicted in Figure. 6.

Figure 6: Image preprocessing

3.4 Modified Sequential-CNN Architecture

The **Sequential Convolutional Neural Network (CNN)** architecture consists of a stack of layers arranged in a linear sequence, where each layer processes the output of the previous layer to learn hierarchical feature representations. This structured design enables efficient extraction of spatial features from input images. The activation of each layer is governed by an activation function g, where w and b denote the weights and biases, respectively, as defined in Eq. (1):

$$a^{[l+1]} = g(z^{[l+1]}), \quad \text{where } z^{[l+1]} = w^{[l+1]}a^{[l]} + b^{[l+1]} \tag{1}$$

In Sequential CNNs, **convolutional layers** apply learnable filters to capture local spatial features such as edges, textures, and patterns. These features are progressively refined across deeper layers, enabling the model to learn complex representations. The use of **Rectified Linear Unit (ReLU)** activation introduces non-linearity, while **pooling layers** reduce spatial dimensions and computational complexity, improving generalization.

Unlike traditional deep neural networks, Sequential CNNs preserve spatial relationships within the data, making them highly effective for image-based tasks. Additionally, techniques such as **batch normalization** and **dropout** are often incorporated to stabilize training and prevent overfitting. The final classification is performed using **fully connected layers**, which map the extracted features to output classes.

The overall transformation performed by the Sequential CNN can be represented as:

$$F(x) = \mathrm{CNN}(x) \tag{2}$$

where x represents the input image and $F(x)$ denotes the predicted output. This formulation illustrates how the model learns a direct mapping from input data to class labels through layered feature extraction and classification.

The Sequential CNN architecture provides a balance between **model simplicity and performance**, avoiding issues such as vanishing gradients commonly observed in very deep networks, while still achieving high accuracy in medical image analysis tasks such as thyroid disease detection.

In Figure. 7, the input of the neural network block is x, and I(x) is the true distribution. The residual is calculated based on the difference between output and input, it is calculated using in Eq. (2)

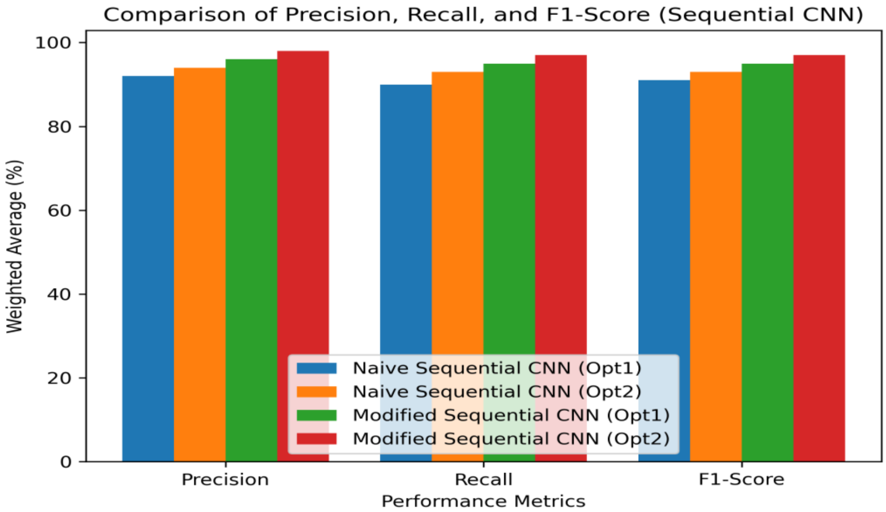

Figure 7: Comparison of precision, recall, and F1-score outcomes

3.4 Enhancement in the Training Using Dual Optimizer

In the proposed system the training is enhanced in ResNet architecture by carrying out batch normalization, activation and Conv2D occurs three times in the residual module where for each time the Conv2D extracts the feature of the image by (1, 1), (3, 3), and (1, 1) respectively. For the first time, Conv2D has already extracted every pixel of the image and also covered every edge of the image by using the (1, 1) matrix. So for the third time instead of extracting the feature by (1, 1), the proposed system extraction of the feature is modified by (3, 3) which helps the model to learn more and give better accuracy. Optimization is one of the important processes in training. Also to improve the accuracy of the proposed system, Stochastic Gradient Descent, and Adam optimization techniques [34] are used in the proposed system. The training is first done using Adam which is the combination of AdaGrad and RMSProp which in turn are the extensions of Stochastic Gradient.

$$w_{t+1} = w_t - \widehat{m}_t \left(\frac{\alpha}{\sqrt{\widehat{v}_t} + \varepsilon} \right) \tag{3}$$

where $= \frac{m_t}{1-\beta_1^t}$ and $\widehat{v}_t = \frac{v_t}{1-\beta_2^t}$

Eq. (4) is the SGD equation to update parameters in neural networks where it reduces the parameter variance which in turn leads to good accuracy.

$$\theta = \theta - \eta . \nabla_\theta J(\theta;\, x,\, y) \tag{4}$$

where θ-is a parameter,η-learning rate,r-is gradient, J-loss function. So the accuracy obtained after using the first optimizer is 94% and after the second optimizer in the proposed system is 97%.

4. RESULT DISCUSSIONS AND OUTCOMES

In this section, the details of the results of a comparative study of the proposed CNN with the Modified ResNet Architecture and the CNN with Naive Sequence CNN Architecture are discussed. The proposed system is validated by conducting experiments implemented using TensorFlow, a deep learning framework performed on a workstation having specifications of 8 GB RAM and an Intel (R) Core (TM) i7 CPU. After collecting various medical images, we augmented the datasets and pre-processed them accordingly. Later the processed images were trained using the Sequence CNN deep neural network in CNN with Adam and SGD as optimizers. In the following section, results of the comparison of Naive Sequence CNN Architecture and proposed modified Sequence CNN Architecture with dual optimizers are discussed. The original data set was increased and there were around 2000 images in the resultant dataset after applying augmentation and pre-processing.

4.1 Performance Metrics

For any effective deep learning model, the prominent process is evaluating the proposed model, certain key classification metrics like Precision, Accuracy, F1-score, Recall, have been computed for the purpose of evaluation of the proposed work. It is based on the totals of the True Positive, False Positive, True Negative, and False Negative. The equations for evaluating these metrics are given below.

Accuracy is the overall percentage obtained for the accurate prediction of the model. It is the most important metric among all and it also determines whether the model is successful or not, it is calculated as follows

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

A Recall is a sensitive rate, in this work it depicts that out of all thyroid affected patients it tells how many it has correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6)$$

Precision is the measure of the model confidence and it specifies patients the model correctly identifies having thyroid disease

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

The harmonic mean of the proposed model's accuracy and recall is F1-score. Higher the classification metrics, the higher the performance of the proposed model.

$$\text{F1 – score} = \frac{2TP}{2TP + FP + FN} \quad (8)$$

4.2 Experiment 1: Proposed Model Evaluation Using Optimizer I

In the first experiment, we have applied an Adam optimization to the modified Sequence CNN architecture to improve the accuracy, and this is the first level of optimization in the proposed system. In the first experiment optimizer, I is applied for the basic Sequence CNN Architecture and the results of this experiment are given in Tab. 2. It is evident from the table that there is an overall accuracy of 88% given by the model. In the next experiment proposed modified Sequence CNN Architecture is combined with the optimizer, I, and the outcomes of the experiment mentioned above are given in Tab. 3. Results clearly show that optimizer I is more effective in modified Sequence CNN compared to the basic Sequence CNN model.

Table 2: Result of basic Sequence CNN Architecture with optimizer 1

Thyroid disease type/metric	Precision	Recall	F1-score	Support
Thyroid cancer	0.95	0.95	0.95	20
Thyroiditis	0.96	0.95	0.95	25
Hyperthyroid	0.95	0.95	0.95	25
Hypothyroid	0.95	0.96	0.95	29
Thyroid nodule	0.95	0.95	0.95	28
Accuracy			**0.9523**	240
Macro avg.	0.95	0.95	0.95	240
Weighted avg.	0.95	0.95	0.95	240

Table 3: Result of modified Sequence CNN Architecture using optimizer 1

Thyroid disease type/metric	Precision	Recall	F1-score	Support
Thyroid cancer	0.96	0.95	0.95	20
Thyroiditis	0.97	0.96	0.96	25
Hyperthyroid	0.95	0.96	0.95	25
Hypothyroid	0.96	0.95	0.95	29
Thyroid nodule	0.95	0.95	0.95	28
Accuracy			**0.9523**	240
Macro avg.	0.96	0.95	0.95	240
Weighted avg.	0.96	0.95	0.95	240

4.3 Experiment 2: Proposed Model Evaluation Using Optimizer II

In Experiment 2, Adam Optimizer with SGD is further used to increase the precision of the model we have proposed to classify the thyroid type of patient and this is considered as level 2 of optimization in this work. In Tab. 4 experimental results of applying basic Sequence CNN with the Optimizer, II is given and the results show that it gives an overall accuracy of 95%, whereas the modified Sequence CNN with Optimizer II is able to give the highest accuracy of 99% and these results are given in Tab. 5. Results clearly indicate that the proposed model gives better accuracy results with both the optimizers over basic Sequence CNN Architecture.

Table 4: Result of basic Sequence CNN Architecture with optimizer 2

Thyroid disease type/metric	Precision	Recall	F1-score	Support
Thyroid cancer	0.99	0.99	0.99	20
Thyroiditis	1.00	0.99	0.99	25
Hyperthyroid	0.99	0.99	0.99	25
Hypothyroid	0.99	1.00	0.99	29
Thyroid nodule	0.99	0.99	0.99	28
Accuracy			**0.9925**	240
Macro avg.	0.99	0.99	0.99	240
Weighted avg.	0.99	0.99	0.99	240

Table 5: Result of modified Sequence CNN Architecture with optimizer 2

Thyroid disease type/metric	Precision	Recall	F1-score	Support
Thyroid cancer	1.00	0.99	0.99	20
Thyroiditis	1.00	1.00	1.00	25
Hyperthyroid	0.99	1.00	0.99	25
Hypothyroid	0.99	0.99	0.99	29
Thyroid nodule	0.99	0.99	0.99	28
Accuracy			**0.9925**	240
Macro avg.	0.99	0.99	0.99	240
Weighted avg.	0.99	0.99	0.99	240

The variation in the values of performance metrics based on different optimizers used in both basic and modified Sequence CNN architecture is plotted as a graph for easy understanding. In the Fig. 7, the precision metric depicts that how precise the model is out of those predicted positive and then the actual positive value predicts how many positive values occurred.

From Fig. 7, it is evident that the fourth classifier Modified Sequence CNN with dual optimizer provides the highest precision of 99% with improvement over the basic Sequence CNN classifier with optimizer 1. It can be seen from the figure that dual optimizers during training give better results in identifying accurate true positives.

Another statistic that illustrates the correctness of the suggested model is recall, which shows that thyroid illness classification is right by indicating the number of true positives vs. the number of true positives and false negatives. It basically displays how many positive values the model has labelled. As shown in Fig. 8, the number of genuine positives from the Naive Sequence CNN with optimizer 1 is the lowest, with an 87 percent recall value, and there is a considerable rise in recall values when the dual optimizer is used.

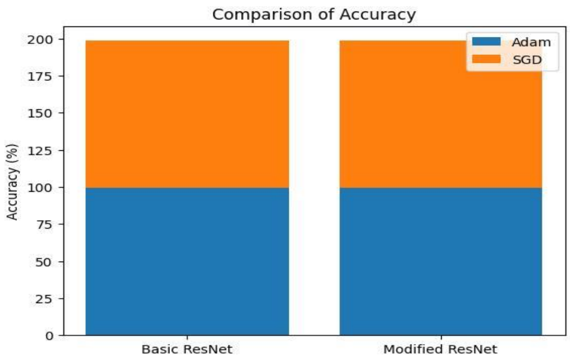

Figure 8: Comparison of accuracy for adam and SGD optimizers

F1-score is another crucial performance parameter that is used to evaluate the efficiency of the model proposed. The harmonic mean of precision and recall is represented by it. F1 score has very significant importance in evaluating the proposed model as the cost of false positives and false negatives have a severe effect. We can see from the above graph that, the dual optimizer-based modified Sequence CNN architecture gives better performance for F1-score over other optimizers. In Fig. 8 comparison of accuracy, recall, and F1-score for all the four models are shown. It can be seen from the figure that the CNN model with modified

Sequence CNN architecture using optimizers in training gives better performance over the basic Sequence CNN architecture.

4.4 Experiment 3: Comparison of Adam and SGD Optimizers

In this to analyze the performance of the optimizers in the experiments were conducted. Now coming to the overall accuracy obtained, the modified Sequence CNN gives a tremendous change in terms of accuracy over basic Sequence CNN. As in Fig. 8, the variation on Adam optimizing the basic Sequence CNN gives lower accuracy than the modified Sequence CNN. After retraining the model with SGD, the modified Sequence CNN gives more accuracy of about 99% whereas the basic architecture attains 95%. It can be noticed that SGD optimizer results in the high accuracy compared to Adam optimizer.

The training loss occurs when the model is being trained and occurs when the model is unable to learn the features. The validation loss, on the other hand, fails to evaluate the projected result. The training accuracy and validation accuracy both determine how much the model has learned and how accurate it is in producing correct results. The model's loss and accuracy data are saved for each epoch. The graph in Fig. 9 shows the number of epochs against training loss vs. validation loss and training accuracy against validation accuracy.

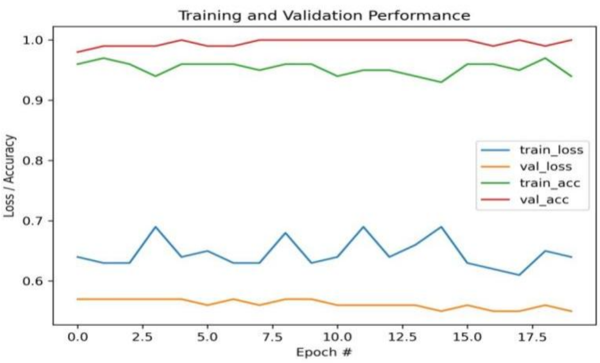

Figure 9: Training loss and accuracy

4.5 Experiment 4: Comparative Analysis of Different CNN Network Architecture

Comparison on other Deep Neural Networks such as ResNet, VGG19, InceptionV3, and Exception over the proposed system has been implemented. The proposed system gave a good accuracy when compared to the other Deep Neural Networks. The comparison is illustrated in Tab. 6.

Table 6: Accuracy comparison of various CNN network architecture

CNN Network Architecture	Accuracy (%)
Sequential CNN	94
InceptionV3	82
ResNet	90
VGG19	84
Xception	88

As shown in the above table, we can find that the performance of Sequential CNN network architecture is superior to InceptionV3, ResNet, VGG19, and Exception. This indicates that the proposed classifier based on the Sequential CNN architecture has resolved the Thyroid disease classification more effectively than the other four classifiers.

5. CONCLUSIONS

This work investigates the methods to improve the CNN-based deep learning algorithm with Sequence CNN architecture. This helps discern the existence of thyroid maladies and helps people take preventive steps to prevent the infliction of the disease. To greatly boost the accuracy of the suggested model for complete categorization of thyroid disease, two optimizers, Adam and Stochastic Descent Gradient algorithm, are proposed. Experiment results indicate that proposed dual optimizer model gives accuracy of 99% which is better than existing algorithm. Also, proposed model outperforms the existing systems in other metrics F1-Score and Recall. In the future, new ways for recognizing more types of cancer regions in the context will be researched. In addition, more research will be conducted to determine how to create a comprehensive and realistic diagnostic report. The results of the investigation on the applicability of several enhanced augmentation approaches with real-time datasets will be examined in the future. The research can also be extended to classify thyroid nodule detection in ultrasound videos and additionally the proposed system can be enhanced to track and observe the changes in the surrounding tissues.

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