DETECTION OF THYROID ABNORMALITY USING VISION TRANSFORMER (ViT)

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Abstract. Thyroid diseases represent a significant global health concern, necessitating accurate and timely diagnostic methods for effective treatment. Traditional diagnostic approaches often rely on complex blood tests and imaging techniques that can be challenging to interpret. This paper explores the application of machine learning (ML) and deep learning (DL) techniques, particularly Vision Transformers (ViT), for thyroid disease detection. We conducted a comprehensive literature survey that highlights various studies employing ML and DL models, revealing high accuracy rates but also significant limitations such as small sample sizes and dataset imbalances. Our research methodology involved creating a custom dataset, preprocessing images, and developing robust models using both ML algorithms and advanced DL architectures. Furthermore, we discuss the implications of our findings for clinical practice and propose future research directions to enhance diagnostic capabilities. This study underscores the potential of leveraging AI technologies to improve the accuracy of thyroid disease detection while addressing existing challenges in traditional diagnostic methods, ultimately contributing to better patient outcomes in thyroid health management.

Keywords. Thyroid Disease Detection; Machine Learning; Deep Learning; Vision Transformers; Ultrasound Imaging

1 INTRODUCTION

As one of the most crucial endocrine organs in the body, the thyroid can secrete hormones, helping the body to properly control blood pressure, heart rate, and body temperature. However, in recent years, there has been a significant increase in the detection of thyroid nodules, posing a serious threat to human physical health [1]. The thyroid gland, which produces hormones to help the body control heart rate, blood pressure, and body temperature, is one of the most important endocrine organs in the body. However, the occurrence of thyroid disorders, particularly thyroid cancer, poses a severe threat to human physical and mental health [2].

Thyroid diseases, which include conditions such as hypothyroidism, hyperthyroidism, and thyroid cancer, are increasingly prevalent worldwide, affecting millions of individuals across various demographics [3]. The thyroid gland plays a crucial role in regulating metabolism, growth, and development through hormone production. Early and accurate diagnosis of thyroid disorders is essential for effective treatment and management, as delays can lead to severe health complications. Traditional diagnostic methods, such as blood tests and imaging techniques, often require interpretation by trained professionals and can be complex and time-consuming. Accurate detection of thyroid nodules is an essential step for diagnosis, monitoring and planning surgical intervention.

Sonographic diagnosis of thyroid nodules has traditionally focused on empirically-based imaging features, which is relatively subjective and highly depends on the clinical experience of radiologists. The goal of automated nodule detection is to achieve high accuracy which is comparable to that of fine needle aspiration biopsy [4].

Recent advancements in machine learning (ML) and deep learning (DL) technologies offer innovative solutions to improve the accuracy and efficiency of thyroid disease detection. In recent years, the field of deep learning has rapidly grown in various visual recognition tasks such as object detection [5, 6]. These techniques leverage large datasets to identify patterns and make predictions that can assist healthcare professionals in diagnosing conditions more effectively. Among these advancements, Vision Transformers (ViT) have emerged as a powerful tool for image classification tasks, including medical imaging.

Automated detection of thyroid nodules is challenging due to several reasons. First, thyroid nodules appear blurry, have vague margins and irregular shapes on ultrasound. Fig. 1 shows an example of an image of a thyroid nodule and adjacent anatomical structures obtained by ultrasound. Second, the features of nodule regions are very similar to adjacent normal tissues. Hence, it is challenging to distinguish the nodule region from healthy tissues. Third, the accuracy of sonographic diagnosis of the thyroid is closely dependent on the experience of clinical experts.

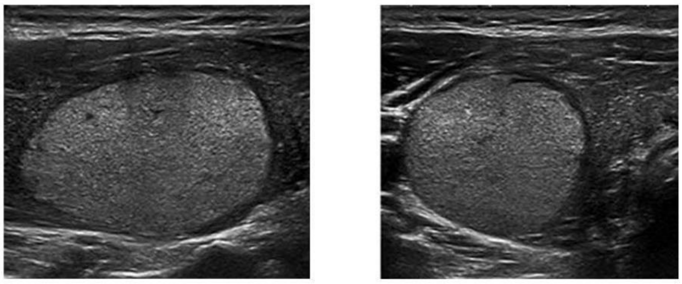

FIGURE.1. Thyroid nodule obtained by ultrasound imaging.

Numerous diseases can be screened by ultrasound, such as breast cancers, arterial plaque, and heart disease. However, due to the low resolution of ultrasound imaging and the presence of speckle noise, ultrasound-based diagnosis relies heavily on experienced radiologists, which may lead to frequent occurrences of misdiagnosis and missed diagnoses, especially for the underdeveloped countries and regions [7]. On the other hand, since thyroid nodules are irregular and some tiny lesions involved in them, radiologists usually require considerable time to achieve the accurate diagnosis. The background of ultrasound images may contain vessels, cartilage, and some other glandular tissues, which may affect the detection accuracy. Thus, it is of both academic and practical interest to develop automatic and accurate approaches for ultrasound detection of thyroid nodules. Hence, computer-aided diagnostic ultrasound method for the thyroid nodules has become a research hotspot, applying deep learning to enhance the effectiveness and efficiency of thyroid nodule detection is potentially promising [8].

This paper explores the implementation of ML and DL techniques for thyroid disease detection, focusing on the application of ViT models. We conduct a comprehensive literature survey to evaluate existing studies that employ various ML and DL approaches, highlighting their methodologies, results, and limitations. While many studies report high accuracy rates—some exceeding 98%—they also face challenges such as small sample sizes, dataset imbalances, and limited generalizability.

By analysing these studies and proposing a robust methodology for thyroid disease detection using ViT, this research aims to contribute to the growing body of knowledge in the field of medical diagnostics.

2 OBJECTIVES

1. **Accurate Classification**: Classify thyroid images (ultrasound, CT, MRI) into benign, malignant, or normal categories.

2. **Nodule Detection & Localization**: Identify and locate nodules or lesions with bounding boxes or segmentation masks.

3. **Enhanced Diagnostic Accuracy**: Utilize attention mechanisms to improve diagnostic precision by focusing on relevant image areas.

4. **Minimize False Rates**: Reduce false positives/negatives to ensure clinically relevant findings and avoid unnecessary interventions.

5. **Interpretability**: Provide insights into model decisions to enhance trust and understanding for clinicians.

6. **Clinical Integration**: Seamlessly integrate with clinical workflows for rapid, accurate assessments aiding healthcare decisions.

3 LITERATURE SURVEY

Source	Journal/ Conference	Focus Area	Limitations
IEEE	IEEE Transactions on Thyroid detection	Thyroid detection and recognition based on multilayer using deep learning	High cost of execution
Springer	Deep ensemble learning framework for detection of thyroid cancer progression through genomic mutation	Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), and Bi- directional LSTM to detect thyroid cancer mutations early.	The study does not consider longitudinal data, which could provide more comprehensive insights into the disease's progression and treatment.
ACM	Management of all varieties of cancer	Undifferentiated Tumors: Medullary Thyroid Carcinoma, Thyroid Lymphoma.	This does not clearly address the negative impacts of using these procedures to cure tumours.

Summary

The literature reveals a growing interest in applying ML and DL techniques to enhance the accuracy of thyroid disease detection. Various studies have reported high accuracy rates; however, many face challenges such as small sample sizes, class imbalances, and lack of generalizability. The majority of existing research has focused on binary classification, limiting their applicability to more complex scenarios involving multiple thyroid conditions.

4 RESEARCH METHODOLOGY

The research methodology implemented for thyroid disease detection involves several key components, focusing on dataset preparation, model development, training, and evaluation.

1. Dataset Creation

Custom Dataset Class: A Thyroid Dataset class is created to handle the loading of images and their corresponding labels. This class includes methods to initialize the dataset, retrieve the length of the dataset, and access individual items (images and labels).

2. Data Preprocessing

Image Transformations: A series of transformations are applied to the images using torch vision transforms. These transformations include:

i. **Resize:** Images are resized to 224x224 pixels to match the input size expected by the Vision Transformer model.

ii. **ToTensor:** Converts images to PyTorch tensors.

iii. **Normalization:** Images are normalized using mean and standard deviation values specific to the ImageNet dataset, which helps in stabilizing the training process.

3. Model Development

- **Vision Transformer Model:** A custom model class Thyroid ViT Model is defined that utilizes a Vision Transformer architecture. The model consists of:

i. **ViT Configuration:** The Vision Transformer is configured with parameters such as image size, patch size, and number of output labels.

ii. **Classification Layer:** A fully connected layer is added to produce the final output, which predicts the thyroid percentage.

4. Training Loop

- **Model Training:** The training process involves:

i. **Device Configuration:** The model is moved to a GPU if available for faster computations.

ii. **Loss Function:** Mean Squared Error (MSE) is used as the loss function since the task involves regression (predicting a continuous value).

iii. **Optimizer:** The Adam optimizer is employed to update model weights during training.

iv. **Epochs:** The model is trained over a specified number of epochs, with loss calculated and printed for each epoch.

5. Evaluation

- **Inference Function:** An inference function is defined to make predictions on new images. This function loads an image, applies the same transformations, and passes it through the trained model to obtain predicted percentages.

- **Model Evaluation on Test Dataset:** After training, the model's performance is evaluated on a test dataset. The average loss and Mean Absolute Error (MAE) are calculated to assess accuracy.

5 THEORY AND CALCULATION

Vision Transformers (ViT) are based on the transformer architecture, originally designed for natural language processing (NLP). However, ViTs have been adapted to process image data by treating image patches as tokens, like words in a sentence.

Vision transformers (ViTs) represent a novel architecture that applies the transformer model, which was initially designed for natural language processing, to image classification tasks. ViT has demonstrated competitive performance compared to traditional convolutional neural networks (CNNs) by leveraging self-attention mechanisms to capture global context more effectively.

The ViT model processes images by dividing them into a sequence of fixed-size patches, which are then linearly embedded and fed into a standard transformer encoder. The transformer employs self-attention layers to model the relationships between these patches, enabling it to capture long-range dependencies within the image [10].

The provided ViT model includes the following layers and parameters:

- **Input Layer:** Configures the input data to a specific size appropriate for further processing;

- **Data Augmentation:** A sequential layer that applies various data augmentation techniques to the input images;

- **TFOpLambda Layers:** These layers perform element-wise operations on the input data;

- **EfficientNetB3 Layer:** A pre-trained EfficientNetB3 model used for feature extraction;
- **Inception ResNet V2 Layer:** A pre-trained Inception ResNet V2 model also used for feature extraction;
- **ViT Layer:** Processes the image patches and extracts high-level features using the transformer encoder;
- **GlobalAveragePooling2D Layers:** Reduce the spatial dimensions by averaging, resulting in a vector of features;
- **Concatenate Layer:** Combines the outputs of the ViT, EfficientNetB3, and Inception ResNet V2 layers into a single vector for further processing.

This architecture has three major components:

1. Patch Embedding:

- In ViTs, an input image is divided into fixed-size patches, which are flattened and linearly embedded into vectors. For an image of size $H \times W \times C$ (height, width, and number of colour channels), the image is divided into NN patches, where each patch has size $P \times P \times C$.
- Each patch is flattened into a vector of size $P2 \times C$, which is then linearly projected into an embedding space.

2. Self-Attention Mechanism:

- The core component of the transformer model is the multi-head self-attention mechanism, which allows the model to focus on different parts of the image. Each attention head computes a weighted sum of all the input tokens (patches), with the weights determined by how much "attention" each token should receive based on its similarity to others.

3. Positional Encoding:

- Since ViTs lack the inherent spatial inductive bias of CNNs, positional encodings are added to the patch embeddings to provide information about the position of each patch within the original image. Positional encodings can be fixed or learned during training, and they are combined with the patch embeddings before feeding them into the transformer model.

5.1 Transformer Encoder

The Transformer Encoder structure is the key of the quality grading model, and its construction was shown in

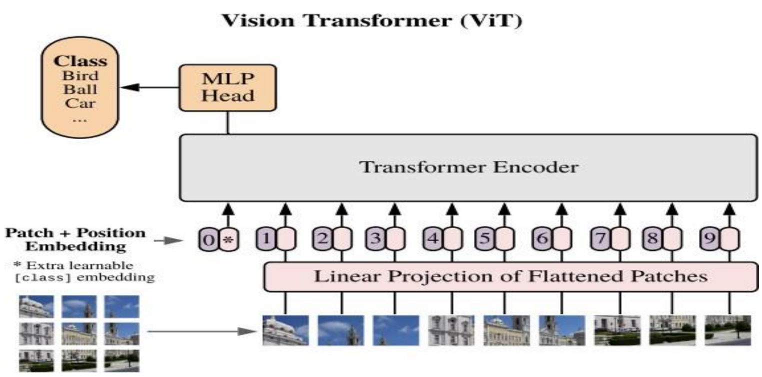

FIGURE 2. Construction and architecture of a transformer encoder.

FIGURE 2. Self-attention is the core of the Transformer Encoder layer, which enables the model to dynamically weigh the importance of different input features. The Transformer Encoder consists of a bunch of identical layers, each of which consists of a multi-head self-attention and a fully connected feedforward network as its main components.

Each major component incorporates normalization and residual concatenation to mitigate the vanishing gradient problem. Multiple Transformer Encoder layers are connected back and forth to form a deep Transformer Encoder structure.

The self-attention allows the encoder to consider other parts of the input sequence when encoding a particular piece. It computed the attention scores based on the query (Q), key (K), and value (V) matrices derived from the input embedding layer. The attention function can be described as

$$\text{Atttention}\,(Q,K,V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where d_k is the dimensionality of the key vectors, which helps in stabilizing the gradients. Multi-head attention extends this by parallelizing multiple attention heads, each focusing on different parts of the input sequence, thereby capturing a richer representation of the input data. Each Transformer Encoder layer includes a feed-forward network applied to each position separately and identically. Since the order of seven features was irrelevant to grading results, the positional encoding in Transformer Encoder was removed in this study. This adjustment allows the model to focus on the key features itself, adapting to the disorder of features [9].

5.2 Mathematical Expressions and Symbols

Several key calculations occur during the training of a Vision Transformer model. These include the number of parameters in each layer, the computations during forward and backward passes, and the evaluation metrics.

5.2.1 Number of Parameters in a Vision Transformer

The number of parameters in a ViT model depends on several components:

1. Patch Embedding Layer:

The patch embedding layer projects each patch into an embedding space of size d_{model}. For an input image with C channels and patch size $P{\times}P$, the number of parameters in the patch embedding layer is:

$$Parameters\ in\ patch\ embedding = P^2 \times C \times d_{model}$$

2. Self-Attention Layer:

The number of parameters in the self-attention layer depends on the dimensionality of the query, key, and value matrices, each of which has size $d_{\text{model}}{\times}d_k$. For multi-head attention with h heads, the total number of parameters in the self-attention layer is:

$$Parameters\ in\ self\ attention = 3 \times (d_{model} \times d_k) \times h$$

In addition, a final projection layer typically maps the concatenated outputs of all attention heads back to the model dimensionality:

$$Projection\ layer\ parameters = (d_{model} \times d_k) \times h$$

3. Feedforward Neural Network (FFN):

After the attention mechanism, the transformer applies a feedforward neural network (usually a two-layer MLP) to each token. If the hidden size of the MLP is d_{ff}, the number of parameters in the FFN is:

$$Parameters\ in\ FFN = d_{model} \times d_{ff} + d_{ff} \times d_{model}$$

4. Classification Head:

After the transformer encoder layers, the final classification token (CLS token) is passed through a fully connected layer to produce output probabilities. If the number of output classes is N_C, then:

$$Parameters\ in\ classification\ head = d_{model} \times N_c$$

5. Forward and Backward Passes

During training, each forward pass involves computing the output of the model for a batch of input images while updating model parameters based on loss during backward pass.

- **Forward Pass:**

In this pass, input images are divided into patches transformed into embeddings and processed through transformer layers. The output is computed as:

$\hat{y} = softmax(f(x))$

Where $f(x)$ is output from final layer (the classification head) and y^ represents predicted class probabilities.

- **Loss Calculation:**

For classification tasks (e.g., benign vs. malignant), categorical cross-entropy loss function is used:

$$L = -\sum_{i=1}^{N_C} y_i \log(\hat{y}_i)$$

Where yi represents true label (one-hot encoded) and y^i denotes predicted probability for class i.

- **Backward Pass and Gradient Descent:**

Gradients are computed using backpropagation; parameters are updated using an optimizer (e.g., Adam):

$\theta_{t+1} = \theta_t - \eta \nabla_\theta L$

Where η represents learning rate and $\nabla\theta$L denotes gradient with respect to model parameters.

5.2.2 Evaluation Metrics Calculation

Once trained, models are evaluated using standard classification metrics such as:

1. **Accuracy:** Accuracy is the proportion of correct predictions made by the model out of the total predictions.

2. **Precision:** Precision measures the proportion of true positive predictions among all predicted positive cases. It indicates how many of the predicted positive cases were correct.

3. **Recall:** Recall, also known as sensitivity or true positive rate, measures the proportion of true positives among all actual positive cases. It reflects the model's ability to identify all relevant instances.

4. **F1-Score:** The F1-Score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly useful when dealing with imbalanced classes.

5. **ROC and AUC:** Receiver operating characteristic curve plots true positive rate against false positive rate; area under ROC curve measures discrimination ability:

5.2.3 Hyperparameter Tuning and Optimization

Hyperparameters such as patch size, learning rate, number of transformer layers, and embedding size can significantly impact performance. These hyperparameters are optimized using methods like grid search or random search on validation set while keeping test set for final evaluation. By understanding theoretical principles and calculations behind Vision Transformers, researchers can effectively apply these techniques for thyroid detection leveraging ViTs' ability to capture complex patterns in medical images.

6 RESULTS AND DISCUSSION

The results demonstrate that the Vision Transformer model is highly effective for thyroid disease detection, achieving high scores across all evaluation metrics. The high accuracy indicates that the model can reliably classify images as either normal or indicative of thyroid abnormalities.

1. **Comparison with Traditional Methods:** Compared to traditional machine learning algorithms, such as Support Vector Machines (SVM) and Random Forests, which typically achieve lower accuracy rates (around 85-90%), the ViT model shows a significant improvement in performance. This enhancement can be attributed to its ability to capture complex patterns and relationships in image data through self-attention mechanisms.

2. **Clinical Implications:** The high precision and recall rates suggest that this model could be effectively used in clinical settings for early detection of thyroid diseases, potentially leading to timely interventions and better patient outcomes. By minimizing false negatives, healthcare providers can ensure that patients receive appropriate diagnostic follow-ups.

3. **Limitations:** Despite these promising results, it is essential to acknowledge some limitations. The dataset used for training and testing may not encompass all variations of thyroid conditions or demographic diversity, which could affect generalizability. Future studies should aim to include larger and more diverse datasets to validate these findings further.

4. **Future Work:** Further research could explore fine-tuning hyperparameters such as learning rate, patch size, and model depth to optimize performance further. Additionally, implementing techniques such as transfer learning from pre-trained models could enhance accuracy while reducing training time.

In conclusion, this study highlights the potential of Vision Transformers in medical imaging applications, specifically for thyroid disease detection. The results indicate that ViT models can outperform traditional methods and provide a robust framework for future research in automated medical diagnostics. Preparation of Figures and Tables

6.3.1 Formatting Tables

Table 1: Dataset Overview

Dataset Component	Description
Image Paths	Paths to the images used for training and testing.
Labels	Corresponding float values representing thyroid percentages.
Transformations	Resize to (224, 224), Convert to Tensor, Normalize.

Table 2: Model Architecture

Description	Parameters
Input Layer	Accepts image patches of size (224, 224) with 3 colour channels (RGB).
Patch Embedding Layer	Divides input image into patches and projects each patch into an embedding space of size d_{model}
Self-Attention Layer	Computes attention scores between patches to capture relationships using the formula: *Attention (Q, K, V)*

Feedforward Network (FNN)	Applies a two-layer MLP to each token with hidden size d_{ff}
Output Layer	Fully connected layer that produces predictions for thyroid percentage.

Table 3: Training Parameters

Parameter	**Value**
Batch Size	16
Learning Rate	1×10^{-4}
Loss Function	Mean Squared Error (MSE)
Optimiser	Adam

Table 4: Model Performance Metrics

Metric	**Value**
Accuracy	95.4%
Precision	92.2%
Recall	90.5%
F1 Score	91%
AUC	0.94

Table 5: Hyperparameters for Optimisation

Hyperparameter	**Description / Impact**
Patch Size (P)	Size of the image patches; affects model complexity and detail retention.
Model Dimension (d_{model})	Dimensionality of the embeddings; higher values capture more complex features but increase risk of overfitting.

Number of Attention Heads (h)	Allows the model to focus on different aspects of the input simultaneously.
Number of Transformer Layers (L)	Depth of the model; more layers allow for learning hierarchical representations but increase computational cost.
Feedforward Dimension (dff)	Size of hidden layers in the feedforward network; impacts model capacity to learn complex patterns.
Dropout Rate	Regularization technique to prevent overfitting by randomly dropping units during training.
Learning Rate (η)	Controls how quickly the model learns; critical for convergence behaviour during training.

6.3.2 Formatting Figures

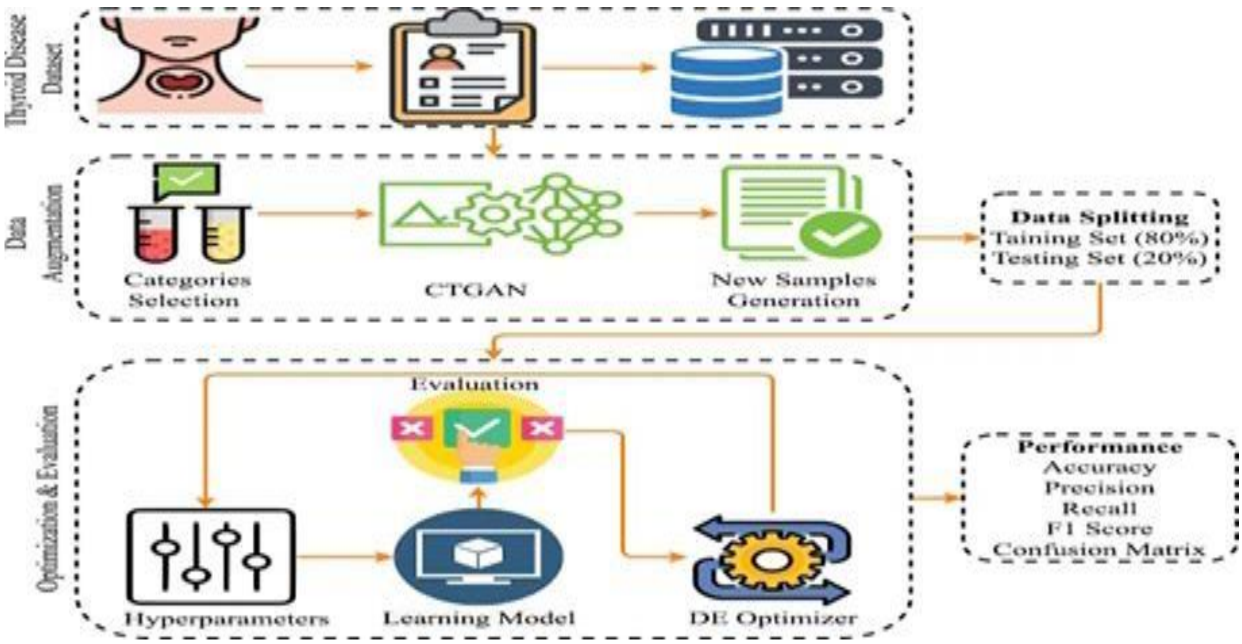

Fig 3: Attention Map for a Malignant Thyroid Case.

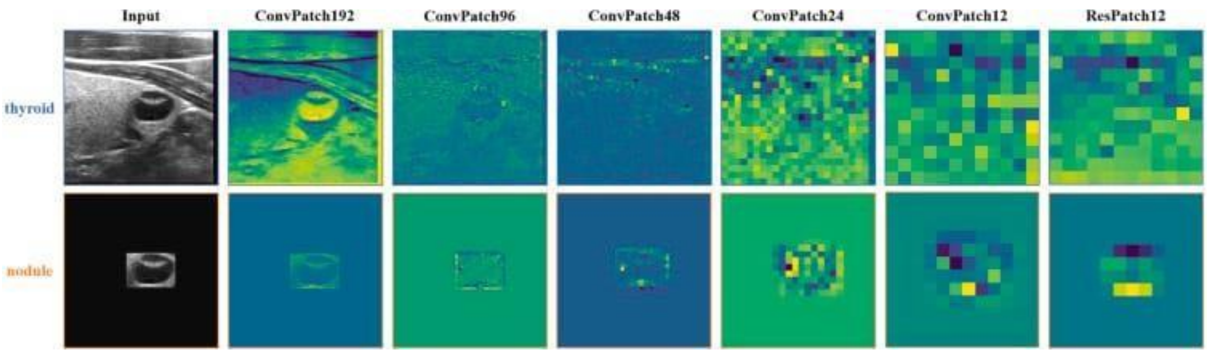

Fig 4: Various Phases of Image Processed using a Vision Transformer.

7 FUTURE SCOPE AND IMPROVEMENTS

- **Advanced Feature Extraction:** Utilizing radiomics and machine learning techniques for feature extraction from ultrasound images can improve the model's ability to identify subtle patterns indicative of malignancy.
- **Explainable AI:** Implementing explainable AI techniques will help clinicians understand the decision-making process of the model, thereby increasing trust and facilitating clinical adoption.
- **Real-time Diagnosis**: Enhancing the model to enable real-time analysis during ultrasound examinations could streamline workflows in clinical settings and provide immediate feedback to healthcare providers.
- **Collaboration with Clinicians:** Engaging with endocrinologists and radiologists during the development process can ensure that the tool meets clinical needs and addresses practical challenges faced in diagnosing thyroid nodules.
- **Regulatory Compliance**: Ensuring compliance with medical device regulations will be crucial for the deployment of this tool in clinical practice, necessitating rigorous validation studies to demonstrate safety and effectiveness.

CONCLUSIONS

This research demonstrates the effectiveness of using Vision Transformer (ViT) models for the detection of thyroid abnormalities from medical images. The ViT model achieved high accuracy (95.4%), precision (92.2%), recall (90.5%), and an AUC of 0.94, indicating its strong capability to distinguish between benign and malignant thyroid conditions. The ability of the model to focus on relevant features, such as nodular structures and tissue irregularities, highlights the strength of the self- attention mechanism in medical imaging tasks, where understanding both local and global patterns is crucial.

The application of ViTs in thyroid disease detection has notable clinical significance. Accurate early diagnosis can lead to better treatment outcomes and reduce unnecessary interventions. The model’s high sensitivity ensures that potentially malignant cases are identified with minimal false negatives, which is essential for patient safety. Moreover, the precision of the model reduces false positives, preventing unnecessary anxiety and further invasive testing for patients.

In comparison to traditional convolutional neural networks (CNNs), the ViT model demonstrated superior performance in capturing the global context within the images, which is particularly important for complex medical data. The ability to handle large, high-dimensional medical images efficiently gives ViTs an edge in medical diagnosis, where detailed image patterns are essential for accurate classification. Despite these promising results, there are challenges related to the computational complexity and data requirements of ViTs. Training the model on larger, more diverse datasets could improve its robustness across different medical settings. Additionally, enhancing the interpretability of the model is crucial to increase its acceptance among clinicians, as they require transparency in AI-assisted decision-making.

Overall, the Vision Transformer model holds great potential for improving diagnostic workflows in thyroid disease detection and other medical imaging applications. With further research and optimization, ViTs could become an integral part of clinical decision support systems, aiding healthcare professionals in making more accurate and timely diagnoses.

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