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Automatic Thyroid Ultrasound Image Classification Using Deep Learning

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Abstract - At the moment, identifying thyroid nodules is mostly done through clinical procedures that need a large workforce and plenty of medical materials. As a result, this study recommends an automated method that combines convolutional neural networks with information about picture texture for identifying thyroid ultrasound nodules. The initial steps are as follows: The collection of both positive and negative samples, image standardisation, and nodule region segmentation are the initial steps in the creation of an ultrasound thyroid nodule dataset. In the subsequent stage, texture features are extracted from the data, features are chosen, and the data's dimensionality is decreased in order to produce a texture features model. Finally, in transfer learning, a feature model of the nodule in pictures is created using deep neural networks. A new nodular feature model called the Feature Fusion Network is created by fusing the texture feature model with the convolutional neural network feature model. The final option is feature fusion. Through the use of a single network for training and performance improvement, a deep neural network diagnosis model is created that can change to fit the features of thyroid nodules. For the purpose of researching this approach, 1874 groups of thyroid nodules discovered by clinical ultrasonography were gathered. Based on Precision and Recall, the harmonic average F-score is used to measure assessment. Feature Fusion Network has an F-score of 92.52% for differentiating between benign and malignant thyroid nodules, according to the experimental data. Our strategy outperforms traditional machine learning techniques as well as convolutional neural networks.

1. INTRODUCTION

The number of thyroid nodules is increasing as people's lives become more stressed. A significant problem involving human health has emerged [1]. It is essential to diagnose thyroid nodules as soon as possible [2]. Ultrasonography, computed tomography (CT), aspiration biopsy, and pathological examination are the techniques that are most frequently used to discover thyroid nodules. The dangerous and costly nuclear scanning required for CT scanning. The thyroid tissue is put under a lot of strain by increasingly frequent and reliable procedures like needle biopsy and pathological testing. They also need a lot of time and additional medical resources to diagnose a patient. Today, ultrasonography is the most popular imaging method for identifying thyroid issues. It is straightforward, repeatable, unobtrusive, effective, and reasonably priced. Typically, a clinician's sole practical skills are exam-based. Clinical experience, which is very personal and prejudice-prone, is what determines whether tumours are benign & malignant. Because of this, it's crucial to be able to rapidly and effectively detect and diagnose the pathophysiology of thyroid nodules found on ultrasonography.

Artificial intelligence technologies have seen a considerable rise in use recently, particularly in the fields of imaging [3]–[5] and signal [6]. An important area of current study is the creation of an automated computer-aided thyroid diagnostic system [7, 8]. This entails knowing how to use ultrasound imaging data. The approach that aids in medical diagnostics most commonly used is engineering for features extraction and classification using classifiers. To eliminate signals, Zheng et al. [9] employed LR (Logistic Regression). The distinction between benign and malignant thyroid cancer was more accurate because to this. With the help of this regression model, it is possible to distinguish between typical and abnormal photos. In order to get accurate diagnosis findings, Liu et al. used the KNN (K-Nearest Neighbour) technique and regional thyroid nodule textural properties. Choi and Choi used thresholds and 3D linked area tagging approaches to help clinicians find genetically specific classifiers. Using computer theoretical systems as a foundation, these technologies offer precise computer diagnostic tools. However, it relies on how accurate the feature texture data is and which classifier is used.

PROJECT OVERVIEW

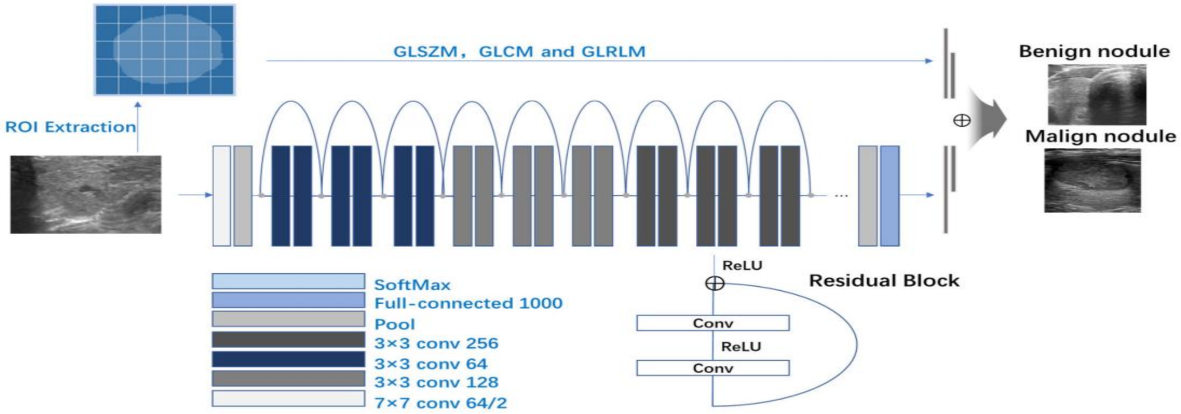
The authors of this article provide a convolutional neural network-based and image texture-based automated technique for thyroid nodule detection during ultrasonography. The following are the primary tasks: Segmenting the nodule region, re-normalizing the images, and collecting both positive and negative samples are all part of the first generation of the ultrasonography thyroid nodule dataset. A texture features model is produced after feature selection, data dimensionality minimization, and texture feature extraction. Following that, a deep neural network using transfer learning generates an image feature representation of the nodule. In order to create the Feature Fusion Network, a new nodular feature model, the feature models from the texture and convolutional neural networks are then combined. The system is trained using a feature fusion network as well as an adaptable deep learning diagnostic model.

LITERATURE SURVEY

Thyroid cancer is getting increasingly frequent, and it is on track to become the fourth most common type of cancer in the world. Thyroid cancer incidence increased by 20% between 1990 and 2013. This global increase in incidence has been attributed to a variety of variables, including earlier tumour detection, a larger prevalence of modifiable human risk factors (such as obesity), and increasing exposure to environmental risk factors (such as iodine levels). We look at both existing and novel ideas regarding how modifiable risk factors and environmental exposures may be contributing to the global rise in thyroid cancer incidence in this Review. Although overscreening and increased detection of possibly clinically insignificant illnesses may have an influence in certain circumstances, other parts of the world may have a greater impact.

2. METHODOLOGY

4.1. MODEL ARCHITECHTURE:



4.2 MobileNet V2: MobileNet-v2 makes use of a convolutional neural network with 53 layers. A network that has previously been pretrained on more than a million photos can be imported from the ImageNet database. The pretrained network is capable of identifying images into 1,000 distinct object categories, including pencils, mice, keyboards, and other animals.

4.3 GAN: To improve prediction accuracy, a machine learning (ML) model known as a generative adversarial network (GAN) pits two neural networks against one another. GANs frequently engage in cooperative zero-sum games unattended and learn new abilities.

4.4 KNN: The k-nearest neighbours algorithm, often known as KNN or k-NN, is a non-parametric supervised learning classifier that relies on proximity to produce classifications or forecasts about how a single data point will be categorised.

4.5 Voting Classifiers: Using a variety of base models or estimators, a machine learning estimator known as a voting classifier learns and predicts the future. The aggregating criterion may be the number of votes for each estimator output.

VGG16: The VGG-16 is a sixteen-layer convolutional neural network. The network may be loaded with a pretrained version that has been trained on more than a million photos from the ImageNet collection. Including keyboards, mice, pens, and animals, the pretrained network can categorise images into 1000 distinct item categories.

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IMPLEMENTATION

1. Steps involved in Proposed system

MODULES:

Data exploration: We will load data into the system with the help of this module.

Processing: We will read data and process it using the module.

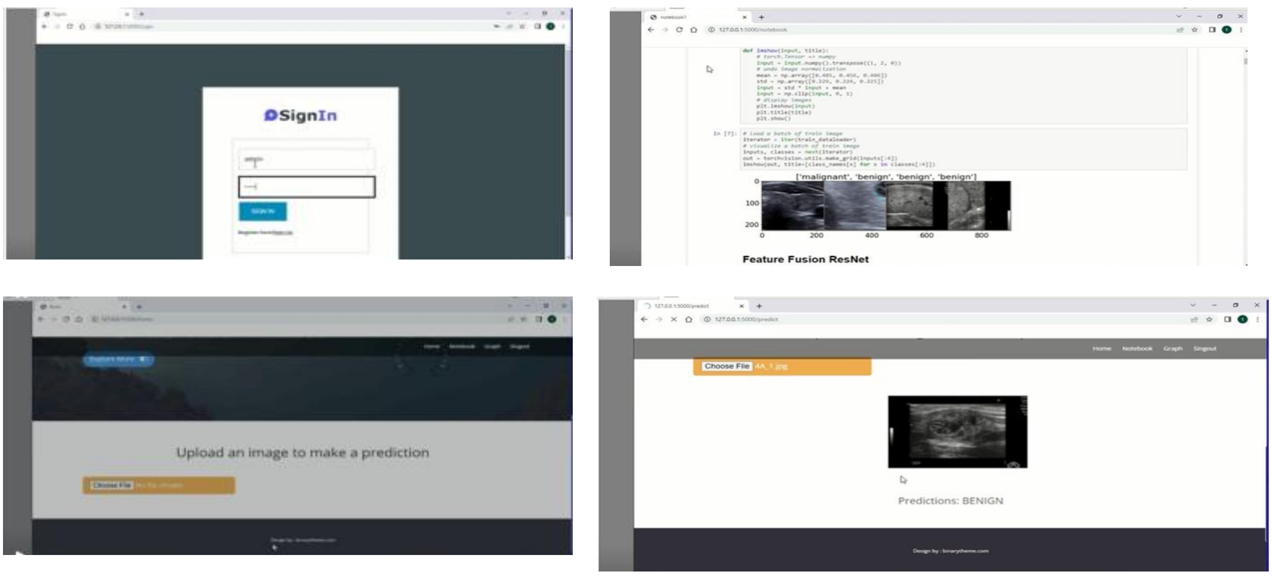
Splitting data into train & test: Data will be separated into train and test groups using this module.

Model generation: Building the model - Feature Fusion ResNet, Feature Fusion VGG16, VGG16 with Feed Forward Network Transfer Learning, ResNet50, VGG16, MobileNet V2 and GAN.

KNN, LR and Voting Classifiers. Algorithms accuracy calculated

- **User signup & login:** Using this module will result in registration and login.
- **User input:** This module will provide data for prediction.

Output:



3. CONCLUSION

This work aims to aid doctors in providing a more accurate and quick examination of thyroid nodules since determining whether a thyroid nodule is benign or malignant using clinical ultrasonography is an arbitrary and time-consuming procedure. Pre-processing is the initial phase, which comprises regions of interest extraction, cropping, and augmentation of the data that were obtained from clinical collection. As a result, it is feasible to create texture characteristics of nodules based on their area, hence reducing the dimensionality of features by using the interaction between features and nodules. In order to further improve the performance of the deep neural network model, the texture characteristics from the earlier stage are integrated. The greatest outcomes were achieved by this technique, according to a study including 1874 thyroid nodule sufferers. Medical applications for it. The advantages of deep neural networks and feature engineering are combined in this research to propose a unique method for feature merging. The transfer learning and fusion feature structure may be used in other domains, such as breast nodules, lung nodules, and other cancer diagnoses, despite the fact that the objective of this work is to enhance the diagnostic performance of ultrasound imaging of thyroid nodules. Incorporating additional features and data into deep neural networks is the aim of feature fusion, it should be highlighted, in order to make the network converge more quickly and accurately. So keep a look out for that. Future fusion data may possibly result from this. The driving forces of the study were image analysis, deep convolutional neural networks, and computer-aided diagnosis.

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