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Deep Learning Approach for Segmenting Nuchal Translucency Region in Fetal Ultrasound Images for Detecting Down Syndrome using GoogLeNet and AlexNet

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ABSTRACT Down syndrome (DS) is a chromosomal disorder linked to intellectual impairment and developmental delays in babies. The primary prenatal indicator for detecting DS during the initial stages of gestation is the thickness of nuchal translucency (NT). This paper introduces a GoogLeNet model based on convolutional neural networks (CNN) for the semantic segmentation of the NT region from ultrasound fetal images, facilitating rapid and cost-effective diagnosis in the early stages of the gestational period. A transfer learning methodology with AlexNet is employed to train the NT regions for the detection of DS. The Inception module of GoogLeNet enables the model to simultaneously capture characteristics at various sizes of images. The capacity to extract both intricate and broad characteristics can improve the model’s performance in precisely identifying the NT area. This will function as an exceptional tool for physicians in screening of DS, enhancing the detection rate and providing a substantial opinion for early diagnosis. The proposed deep learning approach attained an accuracy of 96.18% and Jaccard index of 0.967 for NT region segmentation utilizing GoogLeNet. A confusion matrix was used to evaluate the image classification by AlexNet model's effectiveness, and the results showed an overall accuracy of 97.84%, ROC-AUC of 98.45%, recall of 99.64%, precision of 96.04%, and F1 score of 97.80%. The proposed deep learning method produced remarkable outcomes and can be applied to the identification of DS in medical field. This method identifies individuals at increased risk for this condition and enables termination in the early stages of pregnancy.

INDEX TERMS Down syndrome; Nuchal translucency, Ultrasound.

I. INTRODUCTION

Nuchal translucency (NT) sonography signifies a significant advancement in the screening for Down syndrome (DS). Trisomy 21, characterized by supernumerary chromosome 21, leads to a constellation of clinical manifestations referred to as DS [1]. It is one of the most genetically intricate disorders that may sustain human life beyond term, and it is the most prevalent survivable autosomal aneuploidy. DS is the most prevalent genetic cause of intellectual disability and the primary contributor to certain congenital anomalies and medical disorders. Over the past century, conventional epidemiological investigations have been undertaken to ascertain the frequency, etiology, and clinical relevance of the illness. DS is predicted to occur in around 1 in 732 newborns in the United States, while research suggests variations in incidence estimates across different racial and cultural groups [2]. Ultrasonography is employed for the identification and evaluation of fetuses because to its non-invasive characteristics, cost-effectiveness, and continuous improvement in picture quality [3]. DS can be detected prenatally or postnatally. Prenatal screening comprises biochemical serum analysis and ultrasound examination [4]. In order to find DS, intrusive diagnostic tests like amniocentesis and chorionic villus sampling might cause fetal damage and miscarriage. DS is likely to be linked to a blood test, with signs such as NT and nasal bone (NB) observable in ultrasound scans throughout the first and second trimesters of pregnancy [5]. The integration of maternal age, biochemical serum markers, and sonographic indicators such as NT and NB enhance detection rates [6].

The measurement of NT thickness is a critical prenatal indicator for screening trisomy 13, 18, and 21 [7], [8]. The NT refers to the subcutaneous fluid located beneath the skin, specifically situated behind the neck of the fetus [9]. The epidermis has a white (echogenic) appearance, whereas the NT fluid under the skin looks black (anechogenic). It is assessed between 11th and 14th weeks of gestation during pregnancy. Typically, NT resolves at 14th weeks of gestation . [10, p. 24].. The NT computation necessitates the crown-rump length of the fetus, which should range from 45 to 84 mm [11]. Enlarged NT with a thickness above 3 mm can elevate the risk of heart anomalies and may result in a genetic disorder [12]. The fetus's position must be in the mid-sagittal view to test NT effectively. The physician personally assesses the thickness of NT with the electronic caliper [13]. The calibration is performed by positioning the caliper between two echogenic lines seen on the screen. The NT thickness must be meticulously measured since it falls within a few millimetres; even a minor inaccuracy by the sonographer might result in inaccurate readings. Consequently, automated approaches can enhance the determination of NT thickness and resolve the complications associated with manual measurements.

NT examination is an essential phase of computer-aided diagnosis for the early identification of DS. Conventional segmentation approaches encounter many challenges in recovering the NT area, including ambiguous edges, uniform intensity, prolonged processing time, and a heightened likelihood of mistake [14] . Automated identification of DS would eliminate these obstacles and lead to a more rapid and precise diagnosis of the fetus. The segmentation of NT from ultrasound pictures is a challenging task. There exists a significant overlap between the intensity distributions of NT area clusters and the adjacent background regions. Furthermore, the anatomy of the NT area varies significantly as the fetus rotates. The intrinsic variability in ultrasonic intensity among institutions, scanners, and operators complicates the segmentation process [14].

Numerous studies in the literature address the measurement of NT, notably Bernardino et al. [13], which is among the initial efforts to automate the method. Their approach is semi-automatic since the user must manually identify the membranes around the translucency; they serve as the initial points to be traced along the margins using Sobel and Canny filters. Lee et al. [3] utilized a non-linear anisotropic filter to mitigate potential speckle noise. This approach generally underestimates the thickness of the NT compared to the ground truth established by a doctor. The procedure's application is restricted to photos where the fetus is positioned horizontally. Catanzariti et al. [15] enhanced the cost function for segmenting the edges that define translucency without necessitating beginning parameters. Nirmala et al. [16] first pre-processed sonography images using a median filter to eliminate speckle noise. Then, they identified regions containing the NT and applied the mean shift method to segment that region. Subsequently, the Canny operator is employed on the segmented pictures to delineate the edges that define the NT. They proposed blob analysis to quantify the thickness of translucency. Finally, they have presented a quantitative comparison of the mean thickness values for normal and abnormal translucency. Deng et al. [17] presented a semi-automatic approach wherein images undergo morphological filtering for noise reduction, followed by applying an empirically determined threshold. They designated two initial locations, and the edges are determined from these points using a gradient vector flow snake methodology; the resulting edges are further refined by a dynamic programming process to get the thickness and area of the NT. They presented a comparison of the outcomes obtained from actual and synthetic data. In another study, Deng et al. [18] offered a hierarchical approach for the automated identification of the nuchal area, utilizing three support vector machine (SVM) classifiers to delineate the head, neck region, and body of the fetus. Deng et al. [19] revisited the same strategy by incorporating an additional tier of the hierarchical model to depict the fetal profile, resulting in enhanced performance. Moratalla et al. [7] introduced SonoNT architecture, which is integrated and marketed in some ultrasound instruments. This tool enables semi-automatic assessment of NT, requiring the user to delineate a box that encompasses the maximal thickness of the NT. This tool monitors the upper and lower edges by utilizing gradient and brightness data within the box, ultimately determining the maximum vertical distance between these edges. Supriyanto et al. [20] employed a multilayer neural network to identify the region containing NT by processing sub-samples of the image and determining the degree of association with the NT class. Upon identifying the sites with a greater likelihood of being part of the NT zone, the approach employed an automated algorithm for edge detection based on intensity measurements. This method depends on an initial manual categorization of the mid-sagittal portions, with the ultimate outcomes determined by a correlation index between the average observations from a physician and their respective automatic measures. Park et al. [21] utilized Dijkstra's method to identify the inner and outer boundaries of the two components that define the translucency. They selected seed points inside these areas, and the segmentation graph cut procedure is implemented. Then, the diameter of the NT is assessed. Graphical representations of qualitative evaluations for edge extraction and translucency thickness are presented, highlighting the five best and worst scenarios. Sonia et al. [22] categorized the thickness of both normal and pathological NT with a SVM. Feature extraction is executed by the use of a discrete wavelet transform. This method having limitations such as NT thickness is not quantitatively assessed, the edges are not delineated, and the maximum diameter is not evaluated. Anzalone et al. [23] provide a study focused on the automated identification of the sagittal median and NT measurement. The process has two stages: the first detects the medial sagittal sections, while the second examines the nuchal area and quantifies the NT thickness. Thomas et al. [24] utilized a CNN-based SegNet model incorporating a Visual Geometry Group (VGG-16) for the semantic segmentation of the NT area from US fetal pictures. Chaudhari et al. [25] developed an automated method for NT detection utilizing scale-invariant feature transform (SIFT) key points and a General Regression Neural Network (GRNN) for evaluating NT thickness. Rajesh et al. [26] proposed AdaBoost method for NT region segmentation. Liu et al. [27] developed a CNN incorporating fully connected layers to directly identify the NT area. Additionally, they used U-Net with a tailored architecture and loss function to achieve accurate NT segmentation.

A variety of screening programs utilizing NT sonography are expected to gain popularity for general population screening. Nonetheless, certain practical implementation challenges must be addressed prior to the endorsement of broad employment of this approach. The assessment of the NT necessitates advanced sonographer expertise, and the Fetal Medicine Foundation (FMF) has established a methodology outlining these prerequisites to guarantee accurate measurement [28]. This article aims to introduce an effective tool for facilitating early diagnosis through the automatic measurement of NT.

Deep learning algorithms are highly successful for the classification of many biomedical engineering problems [29], [30],[31]. This paper introduces a GoogLeNet [32] model based on convolutional neural networks (CNN) for the semantic segmentation of the NT region from ultrasound fetal images, facilitating rapid and cost-effective diagnosis in the early stages of the gestational period. A transfer learning methodology with AlexNet [33] is employed to train the NT regions for the detection of DS. GoogLeNet's Inception module allows the model to capture features at multiple scales simultaneously. This is crucial for NT measurement, as ultrasound images may vary in quality and resolution. The ability to extract both fine and coarse features can enhance the model's ability to identify the NT region accurately. In fetal diagnostics, the precise measurement of NT thickness is essential for identifying chromosomal abnormalities such as DS. Conventional manual techniques for assessing NT thickness in prenatal ultrasound pictures may be subjective and protracted, resulting in variability in outcomes.

GoogLeNet, a deep convolutional neural network, provides an effective solution through its capacity to learn and extract hierarchical characteristics from intricate pictures. The application of GoogLeNet for NT measurement in fetal ultrasound images could revolutionize prenatal screening for DS by improving accuracy, reducing human error, and facilitating early detection. This advancement would benefit both clinicians and patients, particularly in settings where access to specialized expertise is limited. Therefore, we have considered the hypothesis that GoogLeNet can automate and refine the accuracy of NT thickness measurements, minimizing human error and enhancing early identification rates of DS, hence improving clinical results.

This study employed the GoogLeNet deep learning architecture for the automated assessment of NT in prenatal ultrasound images to facilitate the early identification of DS. Utilizing the sophisticated feature extraction capabilities of GoogLeNet, we created a model proficient at properly recognizing and segmenting the NT area in real-time ultrasound pictures. Our methodology markedly improves the accuracy of NT region detection, a crucial indicator in prenatal screening for chromosomal anomalies. The incorporation of this deep learning model into the diagnostic procedure provides a non-invasive, dependable, and efficient approach for detecting DS, enhancing prenatal care results. The AlexNet, pre-trained on vast datasets like ImageNet, has already learned to extract hierarchical features that can be leveraged for new tasks, such as NT detection. By applying transfer learning, the model can quickly adapt to identifying features specific to NT with limited training data, common in medical imaging tasks. Additionally, this approach reduces training time and computational resources while improving accuracy, as it builds on the powerful feature extraction capabilities of AlexNet. This may be useful for medical image analysis, where high accuracy is critical for early and reliable DS detection. The main contributions of this study are as follows:

1. A proposal for a novel GoogLeNet-based method for segmentation of the NT region from fetal ultrasound images
2. Segmentation of NT region in fetal ultrasound images using GoogLeNet.
3. Detection of DS from segmented NT regions using the AlexNet.

This paper is structured as follows: Section 2 explains the proposed framework for NT region segmentation and DS identification. The results derived from the proposed framework and the discussion of these results are given in Section 3. The investigation's conclusions are detailed in Section 4.

II. PROPOSED METHOD

In this study, we utilize a GoogLeNet model for the semantic segmentation of the NT region from ultrasound fetal images. Subsequently, we train the segmented images of the NT regions using a transfer learning methodology with AlexNet to detect DS.

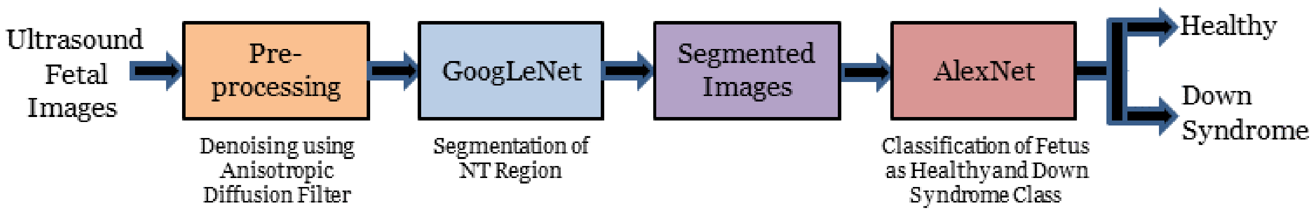

FIGURE 1. The proposed framework for NT region segmentation and DS detection.

The proposed method for detecting DS is shown in FIGURE 1. In this study, we utilize a GoogLeNet model for the semantic segmentation of the NT region from ultrasound fetal images. Subsequently, we train the segmented images of the NT regions using a transfer learning methodology with AlexNet to detect DS. The proposed methodology consists of the following stages: pre-processing of images, applying pre-processed images to GoogLeNet to get segmented NT regions, training of the AlexNet model to get the prediction of DS.

A. DATASET

The dataset utilized in this study was gathered from sonographic centers in Ahmednagar, Maharashtra, India. In this study, we have collected 250 ultrasound images from the first trimester of gestation. A total of 250 ultrasound images have been obtained for this study. Out of these, 50 cases where trisomy 21 (DS) was proven in the first trimester. The results are categorized based on nuchal translucency markers. The dataset is compiled from women aged 25 to 40 years. The annotations were conducted by two experienced radiologists possessing more than 12 years of experience in fetal ultrasound imaging. In cases of discrepancies, a third senior radiologist reviewed the annotations to reach a consensus.

To guarantee quality and clinical relevance, the dataset was assembled using precise inclusion and exclusion criteria. A gestational age between 11 and 14 weeks, when NT measures are most significant clear visibility of the nuchal translucency (NT) area in ultrasound pictures, as well as the availability of associated clinical data verifying the presence or absence of Down syndrome, were prerequisites for inclusion. Low-quality photos with a lot of noise or occlusion, cases with known prenatal abnormalities unrelated to Down syndrome, and records with insufficient clinical details were all excluded.

We have performed 5-fold cross-validation to generate results. The model is trained on four folds and tested on the remaining one, repeating this process five times, each time using a different fold for testing. The final performance is averaged across all five iterations to provide a more reliable estimate of the model's accuracy. This helps reduce overfitting and improves generalization.

B. PRE-PROCESSING

The fetal picture obtained from sonography is affected by noise distortion, which compromises the clarity of local characteristics. Denoising is the preliminary process used to photographs to eliminate noise while preserving background details. The proposed approach employs an anisotropic diffusion filter (ADF) to reduce picture noise [34]. The ADF was selected for ultrasound fetal images due to its efficacy in reducing speckle noise while retaining critical edge details. In contrast to conventional smoothing filters, ADF selectively smooths homogeneous areas while preserving sharp boundaries, essential for maintaining fetal structures. This improves image clarity, facilitating enhanced segmentation and diagnosis. Furthermore, its iterative approach enables precise noise suppression without significant blurring. Anisotropic diffusion is a partial differential equation (PDE)-based technique that reduces image noise without removing significant parts of the image content, especially edges. The anisotropic diffusion filter is modelled as shown in Eq. (1)

$$\frac{\partial I(x,y,t)}{\partial t} = \mathrm{div}[c(x,y,t)\nabla I(x,y,t)] \qquad (1)$$

where I(x,y,t) is the image intensity at position (x,y) and time t; ∇I(x,y) is the gradient of the image at position (x,y), c(∇I(x,y)) is the conductance function, which is a function of the gradient magnitude (i.e., it controls the diffusion rate based on image gradients). It typically decreases as the gradient magnitude increases, meaning diffusion is reduced at edges, div represents the divergence operator, which computes how much the vector field (the gradient-weighted image) is spreading out at each point.

C. SEGMENTATION OF NT REGION USING GoogLeNet

GoogLeNet [32] is a well-recognized pre-trained deep CNN architecture including 22 layers, designed to surpass previous CNN designs. It demonstrated superiority in accurately interpreting visual patterns directly from the source and won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition in 2014. The significant increase in performance is attributed to the inception modules. In this study, we utilize a GoogLeNet model for the semantic segmentation of the NT region from ultrasound fetal images. The GoogLeNet architecture employed for NT region segmentation is as shown in FIGURE 2.

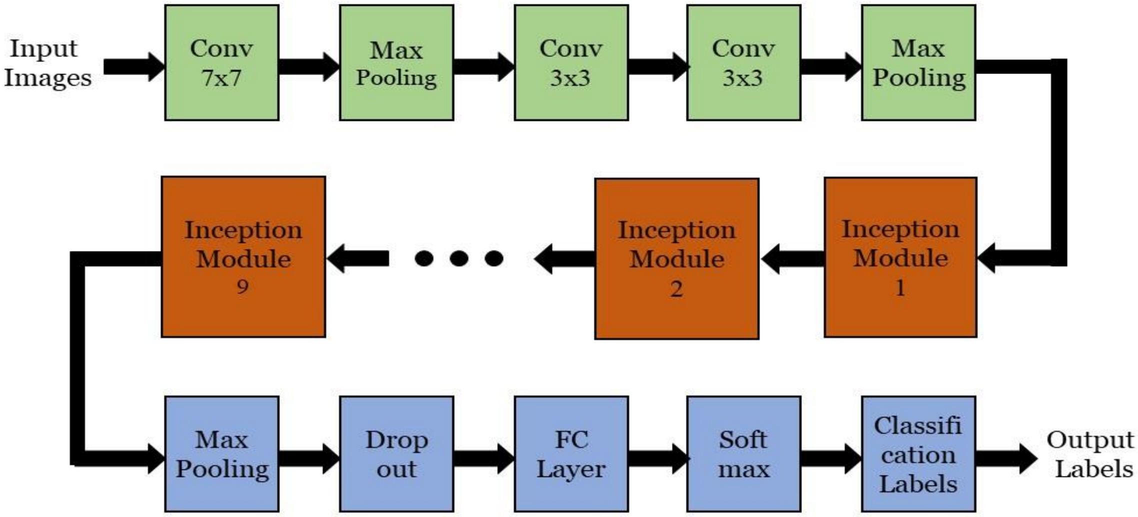

FIGURE 2. GoogLeNet architecture for NT region segmentation

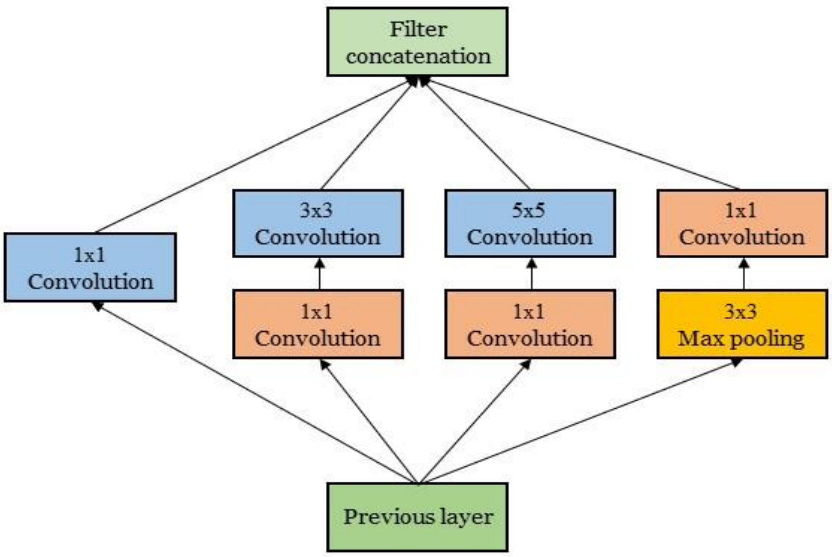

FIGURE 3. Inception module of GoogLeNet

The inception modules used in GoogLeNet architecture is depicted in FIGURE 3. The inception module enables simultaneous execution of numerous convolutions with various kernels and max pooling inside a single layer, ensuring effective weight training and the selection of more pertinent features by the network. Each inception layer has variable-sized convolutional kernels, namely 1×1, 3×3, and 5×5, together with a further 3×3 max pooling operation to extract more specific features from the input received from the preceding layer. The 1×1 filters, in conjunction with the max pooling layer, execute the twin functions of reducing dimension and content summarization from the preceding layer within the inception modules.

An Inception module applies multiple convolutions in parallel with different filter sizes (1×1, 3×3, 5×5) and pooling, then concatenates their outputs. The inception operation on input tensor (X) is given by Eq. (2)

Inception(X):Concat($f_{1\times1}(X), f_{3\times3}(X), f_{5\times5}(X), f_{pool}(X)$ (2)

Where $f_{1\times1}(X), f_{3\times3}(X), f_{5\times5}(X), f_{pool}(X)$ is feature maps from different branches. The nine inception modules of the GoogLeNet reliably extract the most discriminative characteristics from the original picture. The pre-processed images are applied to the GoogLeNet to get the segmented NT regions. We have used learning rate of 0.001, batch size of 16 during training. We have trained model up to 50 epochs with Adam optimizer and cross-entropy loss function. The segmented images are then applied to the AlexNet to categorize them into healthy and DS classes.

D. PREDICTION OF DS USING AlexNet

Among several CNN architectures, AlexNet is one of the most effective frameworks commonly utilized for image classification challenges. AlexNet was introduced by Krizhevsky et al. and secured victory in the ImageNet competition in 2012. It has more than twice the accuracy of

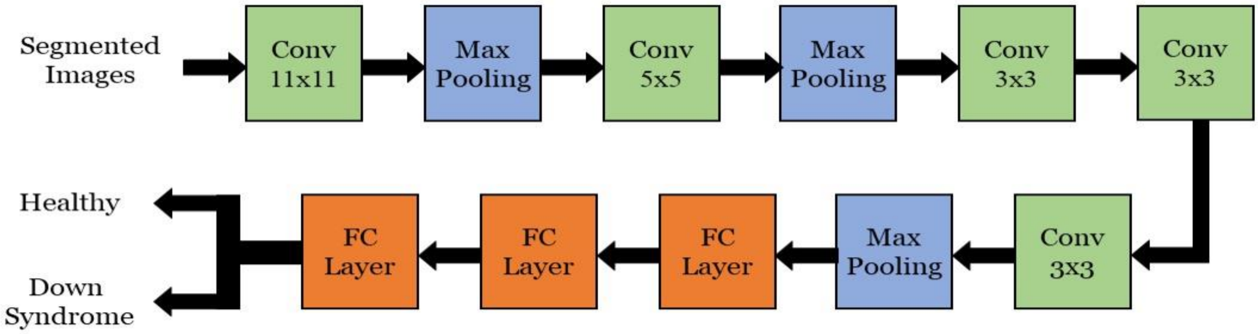

FIGURE 4. AlexNet Architecture for DS detection using segmented NT regions

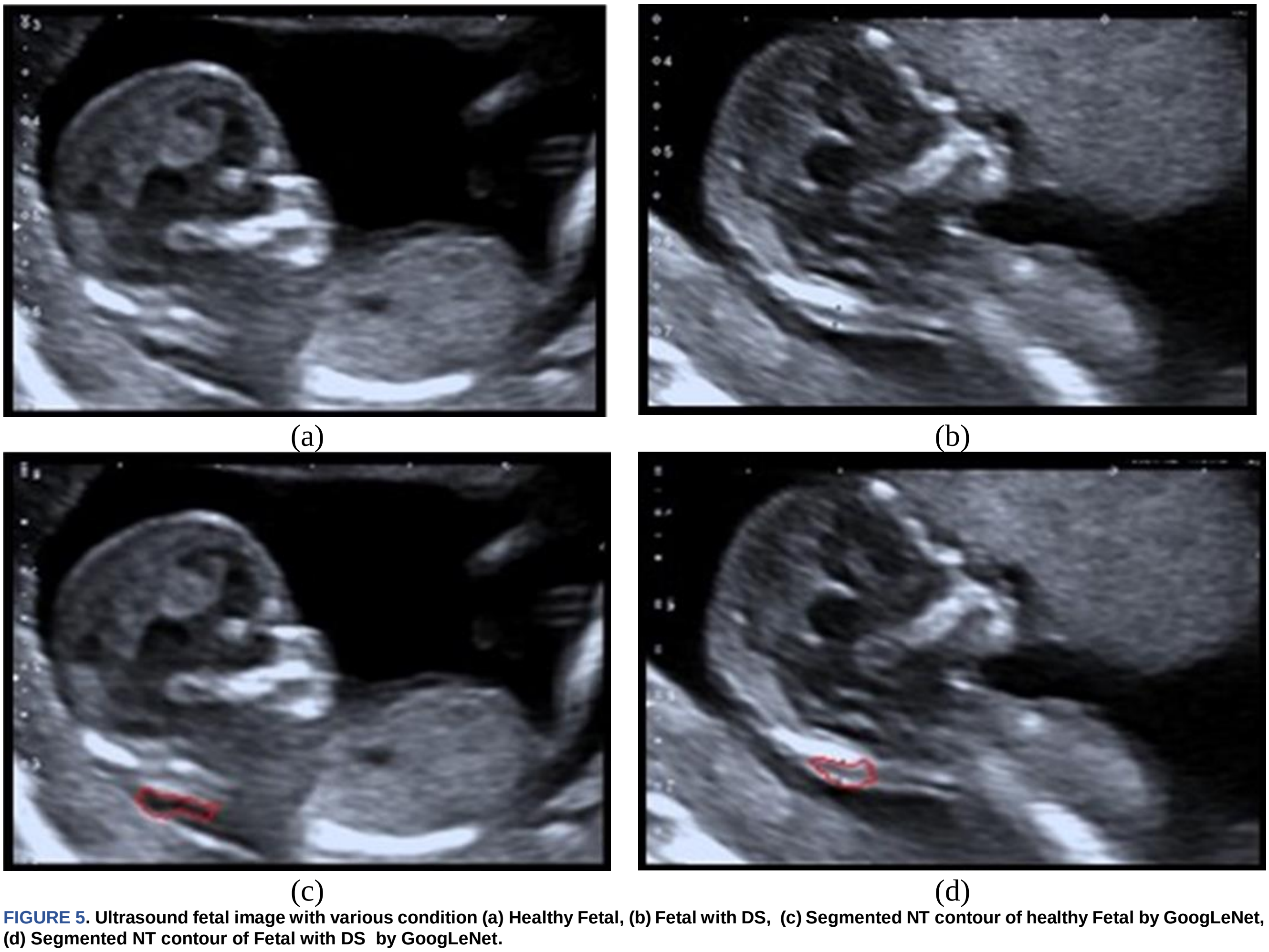

FIGURE 5. Ultrasound fetal image with various condition (a) Healthy Fetal, (b) Fetal with DS, (c) Segmented NT contour of healthy Fetal by GoogLeNet, (d) Segmented NT contour of Fetal with DS by GoogLeNet.

ImageNet and possesses distinct benefits in recognizing images. It is the fundamental model in the field of image processing [33]. AlexNet comprises a total of eight layers in its design, consisting of five convolutional layers and three fully linked layers. Training the network with extensive data enables the achievement of up to 1000 categories of image categorization. The input picture size for the network is 227 x 227 x 3, where 227 denotes the width and height, and 3 signifies the RGB channels. A basic convolutional operation on an image is given by Eq. (3) as follows:

$$O_{i,j}^{(k)} = \sum_{m=1}^{M} \sum_{n=1}^{N} I_{i+m,j+n} .W_{m,n}^{(k)} + b^{(k)} \quad (3)$$

where $O^k$is output feature map for kernel k, i is input feature map, $W^{(k)}$is weights of Kernel k, $b^{(k)}$is bias term M*N: kernel size.

In the conventional AlexNet architecture, the ReLU activation function is incorporated following the first layer, while the maximum pooling layer and normalization are applied after the second layer. The third layer only employs a convolutional layer with a ReLU activation function, whereas the fifth layer resembles the first layer without normalization. The sixth to eighth layers include the fully linked layers, while the final layer use the softmax classifier to categorize the pictures into 1000 classes. Furthermore, Dropout is employed in this study to effectively eliminate parameters in order to mitigate model overfitting. FIGURE 4 shows the AlexNet architecture for DS detection using segmented NT regions. The segmented NT images were utilized to train the AlexNet model for differentiating between the DS and healthy fetus.

The initial four convolutional layers were frozen to retain the low-level feature extraction capabilities learned from ImageNet. The later layers were fine-tuned to learn domain-specific features for NT segmentation. The final classification layer was replaced with a new fully connected layer tailored to our dataset, followed by a softmax activation function. To improve model generalization and mitigate overfitting due to the limited dataset size, extensive data augmentation was applied, including rotation, scaling, and flipping. The network was trained using the Adam optimizer.

III. RESULTS

This work presents a Deep Learning-based method for the automated segmentation of the NT area. A semantic segmentation network utilizing the GoogLeNet framework was developed to segment the NT area. The network's performance was evaluated on DS and healthy fetuses. The GoogLeNet model demonstrated outstanding performance, with an accuracy of 96.18% and a Jaccard index of 0.967. The segmented NT pictures were subsequently trained using the AlexNet model to differentiate between DS and healthy fetuses. Ultrasound fetal images and NT contour segmented by GoogLeNet are shown in FIGURE 5(a)-(d). FIGURE 5(a) and FIGURE 5(b) show the ultrasound images of healthy fetal and fetal with DS. The respective segmented regions of these images by GoogLeNet are shown in FIGURE 5(c) and FIGURE 5(d). The efficacy of the image classification model was assessed via a confusion matrix, resulting in an overall accuracy of 97.84%, ROC-AUC of 98.45%, recall of 99.64%, and precision of 96.04%, and F1 score of 97.80% as presented in TABLE 1. The proposed strategy might be advantageous for physicians in the categorization of DS.

TABLE 1
Confusion Matrix of AlexNet to Differentiate between DS and Healthy Fetuses

	Predicted Class	
Actual Class	Healthy	Down Syndrome
Healthy	99.64	0.36
Down Syndrome	3.96	96.04
Accuracy	**97.84**	

IV. DISCUSSION

To automate the process of NT area segmentation, we presented a deep learning-based method in this research. The NT area was segmented using a semantic segmentation network that was trained on the GoogLeNet model. To further train the segmented NT images to differentiate between the healthy fetus and the one with DS, the AlexNet model was used. The efficacy of proposed deep learning method is analysed by comparing the performance of the proposed method with the state-of-the-art methods as shown in TABLE 2.

TABLE 2
The performance evaluation of the proposed framework with the existing methods.

Research work	**% Accuracy**
Advanced SegNet [24]	91.70
SIFT+GRNN [25]	97.40
AdaBoost [26]	98.60
Cascade ML [27]	95.05
Proposed Deep Learning technique GoogLeNet+AlexNet	**97.84**

Thomas et al. [24] introduced a SegNet model based on a Convolutional Neural Network (CNN) utilizing a Visual Geometry Group (VGG-16) for the semantic segmentation of the NT region from US fetal pictures, facilitating rapid and cost-effective diagnosis in the early stages of gestation. A transfer learning methodology with AlexNet is employed to train the NT divided regions for the identification of DS. They have achieved accuracy of 91.70% for the semantic segmentation of the NT area from US fetal pictures. Chaudhari et al. [25] presented a fully automated approach for NT detection. Initially, deadly head detection was accomplished with scale-invariant feature transform (SIFT) properties. The fetal head was regarded as a crucial reference point for identifying the NT region. We subject the NT region to local refinement and then segment it. They have obtained 97.40% accuracy utilizing SIFT and a General Regression Neural Network (GRNN) for evaluating NT thickness. Rajesh et al. [26] propose a feed-forward artificial neural network utilizing a boosting strategy for the early diagnosis. A network was created with a single layer of concealed neurons and one output neuron. This method relies on facial recognition and the localization of the fetus's facial landmarks. This algorithm predicts the likelihood of DS by calculating the distance between these sites. During their experimentation, facial identification was conducted via AdaBoost, while neural network training was executed using MATLAB. Using this AdaBoost method for NT region segmentation they have achieved 98.60% accuracy. Liu et al. [27] developed a convolutional neural network incorporating fully linked layers to directly identify the NT area. They utilized U-Net with a tailored design and loss function to achieve accurate NT segmentation. Ultimately, NT thickness measurement was determined by principal component analysis. They obtained 95.05 % accuracy NT segmentation using cascaded ML techniques. Conversely, we have achieved accuracy of 97.84% using proposed combination of GoogLeNet and AlexNet deep learning models.

One of the major challenges in applying deep learning techniques, especially in medical imaging, is the restricted accessibility to large and diverse datasets. This limitation can hinder the performance and generalizability of deep learning models. In our study, we addressed this issue by employing transfer learning a method that allows a pre-trained neural network to leverage existing knowledge from a related task and adapt it to a new, but similar, problem. Despite training our model on a relatively small dataset, it still demonstrated outstanding performance in detecting DS.

The implementation of automated DS identification through deep learning offers several important advantages. First, it effectively reduces variability in diagnosis, which often arises due to differences in interpretation between different clinicians (inter-observer variability) or even by the same clinician at different times (intra-observer variability). This automation ensures consistency and repeatability, critical in a clinical setting. Furthermore, the deep learning approach we used is not only technically straightforward but also time-efficient, making it a practical solution for clinical use. By improving the accuracy and speed of detection, this technique can significantly support clinicians by automatically identifying the NT region in ultrasound images and classifying the presence of DS at an early developmental stage. Importantly, this process is entirely non-invasive, requiring no additional effort or procedures beyond standard ultrasound imaging. This both simplifies the task for healthcare operators and strengthens the reliability of the results. Overall, our automated system enhances early diagnosis capabilities by efficiently analyzing ultrasound images to detect and classify DS, providing clinicians with a powerful diagnostic aid.

V. CONCLUSION

The primary aim of this study was to develop a deep learning-based approach for the early classification of Down Syndrome (DS) using first-trimester fetal ultrasound images, with a focus on semantically segmenting the nuchal translucency (NT) region to support early diagnosis and clinical decision-making. The proposed method employed GoogLeNet for NT segmentation and AlexNet for classification. The proposed approach attained an accuracy of 96.18% and Jaccard index of 0.967 for NT region segmentation using GoogLeNet and AlexNet model gives overall accuracy of 97.84%, ROC-AUC of 98.45%, recall of 99.64%, precision of 96.04%, and F1 score of 97.80% for DS detection. It demonstrated promising performance in detecting DS from pre-processed ultrasound images, despite being tested on a limited dataset. The approach achieved high classification accuracy (insert specific accuracy/metrics here if available), indicating its potential as a reliable screening tool for clinical use.

Future directions include expanding the dataset to improve generalization and robustness, integrating NT thickness measurements to standardize the diagnostic process, and exploring advanced deep learning architectures such as transformers or hybrid CNN models. Additionally, domain adaptation techniques will be investigated to enhance cross-device generalization, and large-scale clinical validation will be pursued to ensure real-world applicability and reliability.

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