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Classification of Heart Diseases using Fusion Based Learning Approach

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Abstract: Tetralogy of Fallot (TOF) is a cardiac anomaly characterized by the coexistence of four related heart defects. TOF is most common in children. TOF symptoms include Down syndrome, Alagille syndrome, and DiGeorge syndrome (which causes heart defects, low calcium levels, and poor immune function). A higher risk of getting an infection of the layers of the heart is called endocarditic. This paper presents a novel fusion-based classification model for analyzing ultrasound images. The proposed model integrates multiple components, including the pre-trained VGG19 model, discrete wavelet transform (DWT) for pre-processing, and advanced segmentation models such as 3D-Multi-Chamber Segmentation for region segmentation. An Ensemble classification approach is employed for classifying normal and abnormal ultrasound images. The pre-trained VGG19 model is utilized as a feature extractor to capture high-level features from the ultrasound images. These features are then enhanced using DWT, which effectively decomposes the images into different frequency bands, providing a multi-resolution representation. The model can effectively capture local and global image characteristics by incorporating DWT. To segment the ultrasound images into other regions, the 3D-Multi-Chamber Segmentation model is employed. This segmentation approach leverages the three-dimensional nature of ultrasound images to accurately delineate areas of interest, such as chambers in the heart or structures in the abdomen. The segmented regions provide valuable information for subsequent classification. An Ensemble approach is adopted for the classification task to make accurate predictions regarding the normalcy or abnormality of ultrasound images. The Ensemble classification combines the outputs of multiple classification models, which enhances the overall robustness and performance of the classification process. The proposed fusion-based model offers a comprehensive ultrasound image analysis solution, leveraging various components' strengths. It achieves accurate and reliable classification results by integrating pre-trained models, DWT pre-processing, and advanced segmentation techniques. Experiments conducted on ultrasound images that show the comparative performance of list of algorithms.

Keywords: *Ultrasound image analysis, fusion-based model, VGG19, discrete wavelet transform, DWT, 3D-Multi-Chamber Segmentation, Ensemble classification.*

Introduction

Tetralogy of Fallot (TOF) is a congenital cardiac condition characterized by four distinct cardiac anatomic anomalies. These anomalies include an overriding aorta (where the aorta divides over both ventricles instead of just the left ventricle), a Ventricular Septal Defect (VSD), Pulmonary Valve Narrowing (PVN), and Right Ventricular Hypertrophy (RVH). The most common congenital heart defect in newborns is TOF. Cyanotic heart diseases are characterized by insufficient blood oxygenation, leading to bluish skin and mucous membrane discoloration. Early detection of TOF is crucial to ensure timely medical intervention and appropriate management of the condition. Diagnosing TOF consistently involves various tests that help to analyze the disease status. Several binary and medical image data are used to diagnose the disease by examining the daily activities. However, clinical evaluation alone may not confirm a TOF diagnosis. Figure 1 shows the chambers of the heart which represents the TOF.

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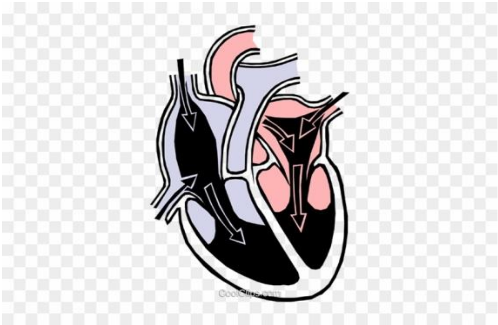

Fig 1: Tetralogy of Fallot (TOF)

Medical imaging techniques such as echocardiography are commonly used to visualize the heart's structure and assess blood flow patterns. Using ultrasonic waves to produce precise images of the heart and its components, echocardiography enables medical professionals to pinpoint the accurate anomalies connected to TOF. In some cases, additional diagnostic tests like cardiac catheterization or magnetic resonance imaging (MRI) can be used to learn more about the structure and operation of the heart. Advancements in medical technology and machine learning algorithms have shown promise in assisting healthcare professionals with TOF detection. Artificial intelligence (AI) models trained on large datasets of TOF cases can aid in automating the analysis of medical images and providing accurate predictions regarding the presence of TOF. These AI models can analyze echocardiograms, MRIs, or other imaging modalities to identify characteristic features of TOF, such as the VSD, narrowed pulmonary valve, right ventricular hypertrophy, and overriding aorta. By providing a reliable and efficient TOF detection tool, AI can enhance diagnostic accuracy and speed up the decision-making process for healthcare providers.

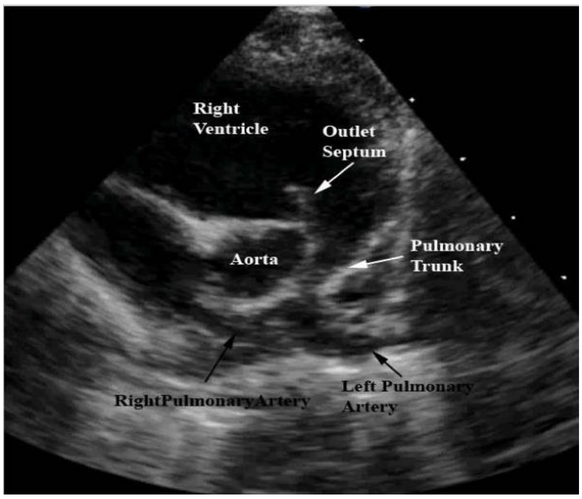

Fig 2: Image shows the affect of TOF

Deep learning is a significant domain that can work on various medical imaging analyses to diagnose several cardiac diseases. One such condition that benefits from deep learning techniques is TOF, a congenital heart defect characterized by four specific abnormalities in the heart's structure. TOF requires accurate and timely diagnosis to ensure appropriate management and improve patient outcomes. Ultrasound plays the major role in analyzing and diagnosis of TOF and other cardiac diseases. It allows clinicians to visualize the heart's structures and functions in real-time, providing valuable insights into the pathology of the condition. Anyhow, the observation of ultrasound images is difficult task and it is depends on clinical experts. This is where deep learning algorithms have the potential to make a significant impact. CNN is an automated learning approach that learns complex patterns and features from large datasets, enabling them to analyze ultrasound images with high accuracy and efficiency. These algorithms can identify and categorize particular cardiac anomalies, such as those found in TOF, by being trained on extensive databases of annotated ultrasound images.

This paper introduced a new fusion-based classification model for evaluating ultrasound images. The proposed model combines multiple elements, including the pre-trained VGG19 model, DWT for pre-processing, and developed segmentation models for region segmentation, such as 3D-Multi-Chamber Segmentation. An ensemble classification approach is used to classify normal and abnormal ultrasound images. The pre-trained VGG19 model is used as a feature extractor to extract high-level features from ultrasound images.

Literature Survey

Zhang G et al. [8] proposed using GANs for dataset image size, shape, and affected regions: A 3D patient PAs by splitting cardiac computed tomography angiography. Each PA's regular and stenotic areas were identified and divided into two sub-groups. The GAN was trained to use these sub-images. In the new patient, an advanced estimated approach helps to improve the patch augmentation. X. Yuan et al. [9] proposed an ML-based prediction model that can predict binary and heart disease with multiple classifications at once. To improve the generalization of binary classification prediction and decrease data complexity, a fuzzy-GBDT algorithm that blends GBDT and fuzzy logic must first be developed. It integrates the

Fuzzy-GBDT and bagging and aids in overcoming over-fitting. The multi-classification prediction, in the end, further classifies the severity of heart disease. A novel disease detection model that can address several problems with ML and DL algorithms was proposed by Rohit Bharti et al. [10]. The 14-attribute UCI heart disease dataset was subjected to these algorithms. Finally, the proposed approach shows a massive performance in terms of accuracy. G. Yang et al. [11] introduced the new CPS-based HRS that analyzes the significant patterns between the patient health care systems. C. Li et al. [12] proposed a novel EMR data management system that combines blockchain technology. The proposed approach mainly balanced the data collected from various distributed systems that help manage the EMR data. The proposed approach focused on providing security with healthcare, which is an integrated approach. A novel approach that monitors health in three stages was proposed by Y. Cheng et al. [13]. Time and frequency-based analysis is used in the first feature extraction stage to ensure accurate feature extraction. In the second stage, the AKSC approach is used to find the malicious activities among the systems based on the updated approach. Finally, the new LSTM-RNN is developed to predict the system failure time based on the outcomes. R. Tao et al. [14] introduced an accurate healthcare analysis system that diagnoses diseases in their early stages. J. Li et al. [15] discussed the classification of various algorithms based on feature selection in heart disease detection in the early stages. The existing approaches observe the feature selection issues in finding accurate health patterns. The proposed approach increases the classification accuracy and decreases the classification and computation time. Based on the fine-tuned parameters, the proposed approach obtains high accuracy. P. Chotwani et al. [16] introduced the automated framework that specifies several issues addressed in healthcare monitoring systems. The proposed approach is a dynamic system that helps experts in diagnosing diseases. It also reduces the computation time and increases the accuracy based on disease detection. A novel method that increases the significance of identifying the features of heart disease detection was proposed by S. Mohan et al. [17]. Based on the classification, 88.7% accuracy was achieved by the suggested system. Edupuganti et al. [18] presented the new heart disease classification approach that combined with deep learning models. The LeNet-10 contains 10 layers that help to classify the heart disease into two types: normal and effected samples. Abdellatif et al. [19] presented a new model that identifies heart disease using the infinite feature selection that helps identify the significant features by combining the IWRF with Bayesian optimization to fine-tune outcomes. The proposed approach uses the two publically available datasets that help to achieve better accuracy over disease detection rate. The accuracy is improved up to 2.5 and 4.7 for two datasets. Fitriyani et al. [20] presented an effective heart disease prediction model that contains the DBSCAN to remove the outliers by combining the SMOTE-ENN to train the dataset with the XGBoost model. The experiments are conducted using two heart disease-based datasets and comparing the proposed approach with several ML algorithms. The suggested system performs well when compared to current techniques. The first dataset obtained 95.78%, and the second obtained 98.45% accuracy. Ishaq et al. [21] predicted the classification model that predicts heart diseases based on heart failures. Two hundred ninety-nine patients who were admitted to the hospital provided the data. The suggested method used an efficient feature extraction technique that resolves dataset imbalance by extracting essential features. The comparison between various ML algorithms is shown in this paper. Finally, the proposed approach obtained an accuracy of 0.9263. Gupta et al. [22] proposed an intelligent system that predicts heart diseases from the UCI dataset. The proposed method combines with FAMD to extract the significant features from the given dataset. The results show the high performance for the proposed MIFH, which is 96.56%. Khan et al. [23] presented the MSSO-ANFIS approach that, combined with a feature extraction technique, focuses on critical factors from the medical data analysis. The proposed approach improved the performance by adopting the search-based algorithm called the Levy flight algorithm. The parameters obtained from the proposed method are optimized to get better outcomes. The data collected from patient health records analyzed the heart condition with an accuracy of 99.45%. Khan et al. [24] introduced the IoT system that diagnoses heart disease inaccurately. To overcome this issue, the IoT is integrated with modified DCNN by using the continuous health monitoring system with the smart-watch attached to the patient, which analyzes the BP and heart rate. The MDCNN used the patient data to classify normal and abnormal patient records. Finally, the results show the disease detection rate is high, at 98.45%, which is better than existing systems. Bashar et al. [25] presented a new point care plot that extracted the unique heart rate that solves the issues identified in heart image processing. The proposed approach is integrated with various feature extraction techniques that remove the significant features from the given dataset. The final accuracy of the proposed method is about 99.34%, which is better than existing systems. Sakib et al. [26] presented the AI-based pipeline approach that combines the two AI-based models such as M1 and M2. M1 works as a pre-processing technique, and M2 is used as the ultra-edge IoT sensor that simulates heart disease detection. The author of this paper wants to diagnose heart arrhythmia from ECG samples. M2 also focused on obtaining accurate features from the given input datasets. The outcomes show the exact disease detection rate, which is better than existing models. Esther et al. [27] presented the nnU-Net segmentation approach that extracts the segmentations from the given heart cardiac cycle from the two types. The multi-model DL classifier predicts CRT by combining the segmentation approaches with two models. Finally, the proposed approach is high compared with previously used models. Leclerc et al. [28] presented the new cardiac structures that predict the abnormalities in the patient samples. The patient samples are Ultrasound images that consist of a fully annotated dataset for analyzing the patient's heartbeat. The proposed approach combined various techniques that find the end-diastolic and systolic volumes that reduce the error rate.

Dataset Description

The dataset used in this study came from Echonet-Dynamic. There are 250 ultrasound images for testing and 750 ultrasound images for training. The Tetralogy of Fallot (TOF), which is thought to be a cardiac condition, can be found using these pictures.

Table 1: Normal and Abnormal Samples of Dataset

Dataset images	Normal	Abnormal
Training	542	208
Testing	154	96

VGG-19 for Pre-trained Model

The VGG-19 is the pre-trained model that trains the complex image patterns. Recently many image processing techniques are applied on medical images to detect or find the heart diseases. The application of deep learning models, such as VGG-19, to heart ultrasound images holds significant potential for improving the accuracy and efficiency of diagnostic processes. Echocardiography, another name for heart ultrasound, is a common imaging technique used to evaluate the anatomy and function of the heart [29]. It provides valuable information about nature's chambers, valves, and blood flow patterns. However, analyzing these images manually can be time-consuming and subjective, relying heavily on the expertise of the interpreting physician. By leveraging the capabilities of deep learning models, like VGG-19, we can automate the analysis of heart ultrasound images and potentially enhance the accuracy and consistency of diagnoses. With a deep architecture of 19 layers, the VGG-19 model has shown exceptional performance in image recognition tasks after being trained on a sizable dataset of real-world images.

To adapt the VGG-19 model for heart ultrasound image analysis, we need to fine-tune it using a specialized dataset of labeled ultrasound images. This dataset should include a variety of normal and abnormal cases, covering different heart conditions and variations in image quality. Fine-tuning involves adjusting the model's weights and biases to make it more specialized and optimized for heart ultrasound images [30].

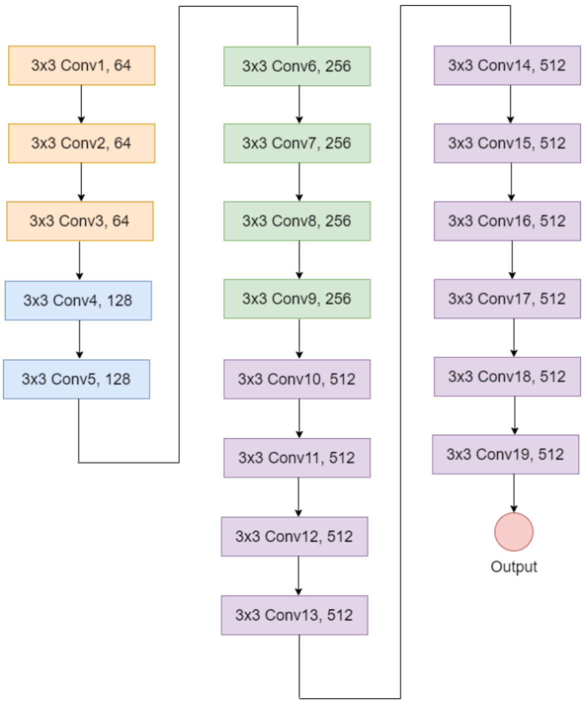

Fig 3: VGG-19 for Pre-trained on Cardiac Images.

The advantages of using the VGG-19 pre-trained model for heart ultrasound image analysis are numerous. First off, the deep architecture of the model enables it to extract intricate patterns and features from the images, which can help with precise abnormality identification. Second, the pre-trained weights provide a strong initialization, enabling the model to converge faster during training. Finally, the transfer learning approach, using pre-trained models like VGG-19, can reduce the need for a large annotated dataset, as it leverages knowledge learned from a different but related task. The pre-trained CNN that has been applied extensively to image classification tasks is the VGG-19 model. Convolutional, pooling, and fully connected layers are among the 19 layers that make it up.The overview of the layers in the VGG-19 model:

Input layer: This layer takes the ultrasound image as input.

Convolutional layers: The VGG-19 model contains a series of convolutional layers with different filter sizes and depths. These layers learn local features and capture the spatial information present in the ultrasound image.

Pooling layers: Following every group of convolutional layers are max-pooling layers, which reduce the feature map's physical dimensions while retaining the most essential data.

Fully connected layers (FCL): The last few layers of the VGG-19 model consist of fully connected layers. These layers aggregate the features learned by the convolutional layers and make predictions based on them.

Output layer: The final layer of the VGG-19 model produces the prediction for heart disease. It typically uses a sigmoid activation function, depending on whether it's a binary classification or multi-class classification problem.

A vector of inputs $x = [x_1, x_2, \dots x_n]$

The softmax activation function is defined as:

$$\mathrm{softmax}(x_i) = \frac{\exp(x_i)}{\mathrm{sum}(\exp(x_j))} \text{ for } i = 1 \text{ to } n,$$

Where $\exp(x)$ represents the exponential function and $\mathrm{sum}(\exp(x_j))$ is the sum of the exponential values for all elements in the input vector x.

To adapt the VGG-19 model for heart disease prediction with ultrasound images, you would replace the output layer with a new layer that matches the number of classes in your specific problem (e.g., healthy vs. diseased) [31]. You would then fine-tune the model by retraining the last few layers or more, depending on the size of your dataset.

Discrete Wavelet Transform (DWT) For Ultrasound Images with equations

A popular method for analyzing signals and pictures is the DWT. It breaks down a sign or image into constituent frequency components, making representation and analysis more effective. The basic equations for performing the DWT on ultrasound images. A grayscale ultrasound image of size NxN, denoted as f(x, y), where x and y are the spatial coordinates. The DWT operates on this image by decomposing it into multiple levels or scales. The DWT decomposes the image into four components: approximation coefficients (LL), horizontal detail coefficients (LH), vertical detail coefficients (HL), and diagonal detail coefficients (HH). These components represent different frequency content at different scales.

To compute the DWT, we can follow the steps outlined below:

Choose a wavelet function, such as Haar, Daubechies, depending on the specific application requirements.

Establish the wavelet (high-pass) and scaling (low-pass) filters connected to the selected wavelet function. It will refer to the wavelet filter as g(n) and the scaling filter as h(n). Start with the original image, f(x, y), at level j=0. Apply the low-pass, h(n), and high-pass filter, g(n), to each row and column of the image.

For the approximation coefficients at level j, denoted as LL (j), compute:

$$LL(j) = h * f * h^T$$

Here, h represents the filter coefficients, f is the original image, and h^T denotes the transpose of the filter.

For the horizontal detail coefficients at level j, denoted as LH (j), compute:

$$LH(j) = h * f * g^T$$

Here, g represents the wavelet filter coefficients.

For the vertical detail coefficients at level j, denoted as HL (j), compute:

$$HL(j) = g * f * h^T$$

For the diagonal detail coefficients at level j, denoted as HH (j), compute:

$$HH(j) = g * f * g^T$$

Repeat the above steps for each level of decomposition desired. Typically, the number of levels is determined by the application and the desired level of detail. After obtaining the LL, LH, HL, and HH coefficients at each level, you can further analyze or process these components based on your specific needs.

3D-Multi-Chamber Segmentation model

One kind of DL model used in heart ultrasound image analysis to segment and define various functional or anatomical regions within a three-dimensional (3D) medical image is the 3D Multi-Chamber Segmentation model. It is frequently used with medical imaging modalities, such as ultrasound scans, to distinguish and identify different human heart structures, especially regarding heart segmentation. The model is built as a DNN and is frequently based on a CNN with sophisticated architectures such as 3D U-Net and V-Net. These networks can effectively capture the spatial relationships between voxels or 3D pixels, which make them ideal for processing 3D data.

$$DiceLoss = 1 - \frac{2 \cdot |A \cap B|}{|A| + |B|}$$

A- Predicted segmentation mask.

B- Ground truth segmentation mask.

|A| and |B| are the cardinalities of the predicted and ground truth masks, respectively.

Note: The loss is computed for each chamber in the segmentation task, which is aimed to minimize this loss during training.

Evaluation Analysis of Pre-trained Models

In deep learning, two critical metrics are used to assess a model's performance during and after training: training and testing loss. The training loss in this paper quantifies how well the suggested VGG19 fits the training set. It measures the discrepancy between the target values in the training dataset and the model's predictions. To minimize this loss function during training, the VGG019 parameters (weights and biases) are changed, improving the VGG-19's ability to fit the training set. The training loss usually goes down as training goes on. A decreasing training loss suggests the model improves its learning ability from the training set.

A loss test quantifies how well a trained model translates to new data. In a different validation or testing dataset, it measures the discrepancy between the model's predictions and the actual target values. The testing loss is a valuable tool for evaluating the model's predictive power on data not used in training. It is a crucial metric for assessing how well a model generalizes. A low testing loss would be ideal since it would suggest that the model can produce precise predictions on fresh, untested data. Excessive testing loss may indicate over-fitting, a condition where the model works well with training data but poorly with new data. Comparing the testing loss of VGG-19 to that of other systems, like VGG16 and RESNET50, is low.

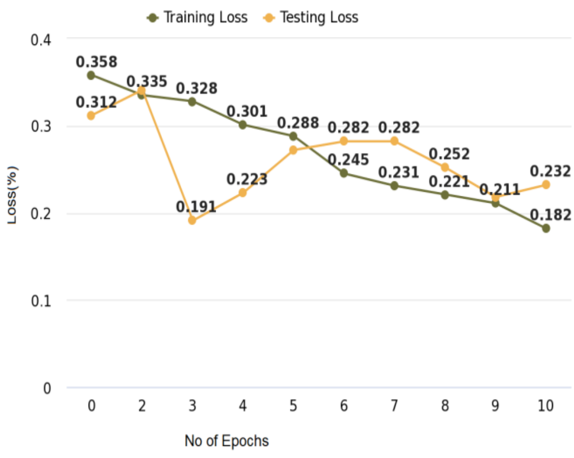

Fig 4: Performance of VGG-19 based on Training and Testing Loss

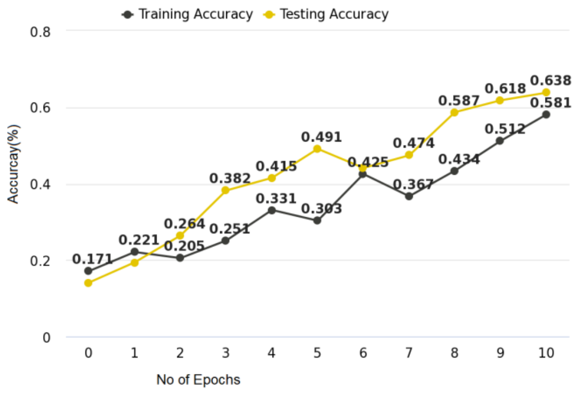

Fig 5: Performance of VGG-19 based on Training and Testing Accuracy

Fusion Based Learning Approach combined with RNN to detect heart vein blockage

The other name for heart vein blockage is coronary artery disease (CAD), an abnormal medical condition that prevents blood circulation among the heart muscles based on the narrowed blockage [32]. Timely detection and diagnosis of heart vein blockage are crucial for effective treatment and prevention of potential complications. Recently many advanced ML methods have been introduced to detect heart diseases and improve accuracy. One such approach is the fusion-based learning approach, which combines multiple sources of information to enhance the performance of the model. In this context, combining the fusion-based learning approach with recurrent neural networks (RNNs) can offer a powerful solution for detecting heart vein blockage. Because RNNs are a particular kind of neural network that can handle sequential data, they are a good choice for analyzing time-series data in the medical field.

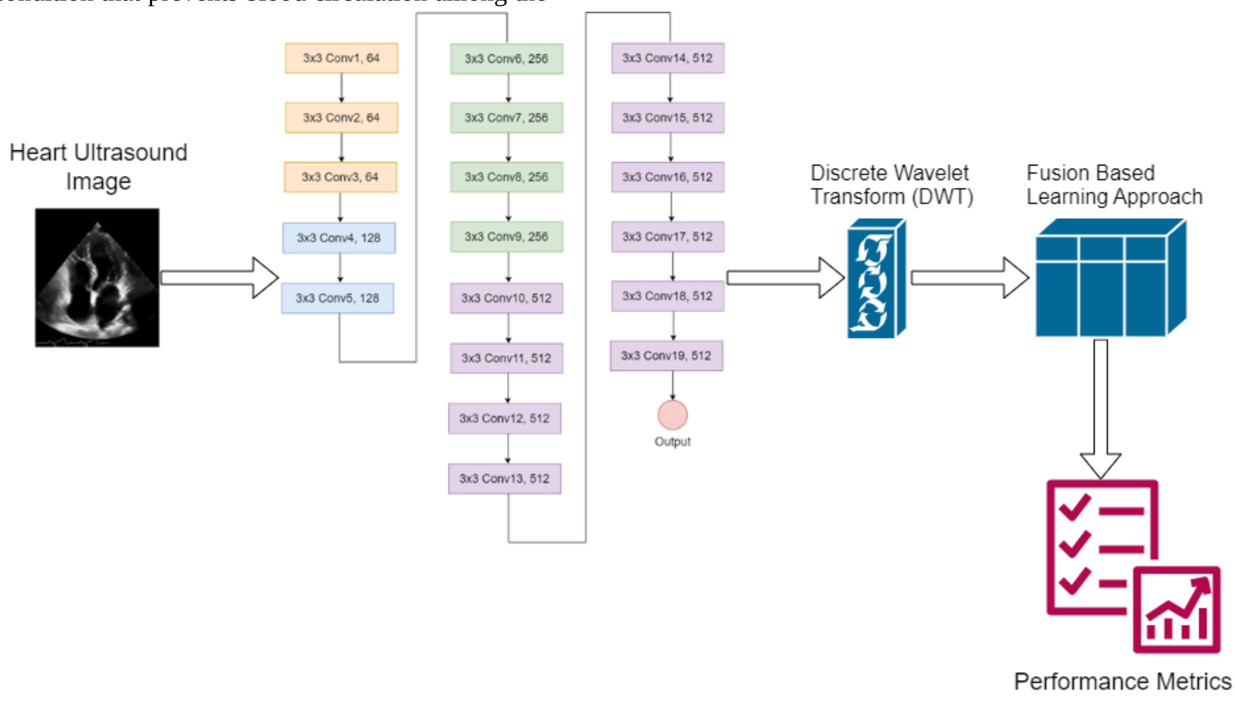

Fig 6: Architecture Diagram

The fusion-based learning approach involves integrating multiple types of data or features to improve the learning and predictive capabilities of the model. In the case of heart vein blockage detection, various data sources can be leveraged, such as electrocardiogram (ECG) signals, patient demographic information, medical history, and imaging data like angiograms. By fusing these different types of data using appropriate fusion techniques, the model can extract complementary information and capture complex patterns that may not be evident from a single data source alone. This can enhance the accuracy and robustness of the heart vein blockage detection system.

Additionally, the integration of RNNs in the fusion-based learning approach allows the model to effectively capture temporal dependencies and patterns present in the sequential data. RNNs can learn from the historical information and leverage it to make accurate predictions about the presence or severity of heart vein blockage. The combination of fusion-based learning and RNNs presents a powerful approach for heart vein blockage detection, as it leverages multiple data sources and sequential information to provide a more comprehensive analysis. This comprehensive approach can improve diagnostic accuracy, facilitate early intervention, and ultimately improve patient outcomes. In the following sections, we will delve deeper into the methodology and techniques employed in this fusion-based learning approach combined with RNNs for heart vein blockage detection.

The Fusion Based Learning Approach combined with RNN (Recurrent Neural Network) can be represented using the following equations:

Fusion-based Learning Approach:

The fusion-based learning approach aims to combine information from multiple sources or modalities to improve learning performance. It can be represented as follows:

$O = (X_1, X_2, X_3, \ldots, X_n)$

Where:

O represents the fused output

$X_1, X_2, X_3, \ldots, X_n$ represent the input from different sources or modalities

f denotes the fusion function that combines the inputs to produce the fused output.

Recurrent Neural Network (RNN):

RNN is a type of neural network that is designed to handle sequential data by capturing the temporal dependencies. The equations for a basic RNN can be represented as follows:

$y_t = (Wyy_{t-1} + Whh_{t-1} + b)$

$a_t = (W_a a_{t-1} + b_a)$

y_t - the output at time step t,

y_{t-1} - the output at the previous time step,

h_{t-1} - the hidden state at the previous time step,

a_t represents the activation at time step t,

Wy, Wh, W_a are the weight matrices,

b, b_a are the bias vectors,

g is the output activation function, and

f is the activation function for the hidden state.

Combined Fusion and RNN:

To combine the fusion-based learning approach with RNN, we can feed the fused output from the fusion approach as input to the RNN. The equations for the combined approach can be represented as follows:

$y_t = (Wyy_{t-1} + Whh_{t-1} + Wf fusedO + b)$

$a_t = (W_a a_{t-1} + b_a)$

Where:

Wf is the weight matrix for the fused output from the fusion approach.

These equations represent the combined fusion-based learning approach with RNN, where the fused output is incorporated into the RNN to capture the sequential dependencies and improve learning performance by leveraging information from multiple sources or modalities.

Performance Metrics

Based on the following examples, displayed in Figure 7, the confusion matrix evaluates the effectiveness of the suggested model. We can assess the model's advantages and disadvantages using the provided metrics and determine whether to change the model or gather more information.

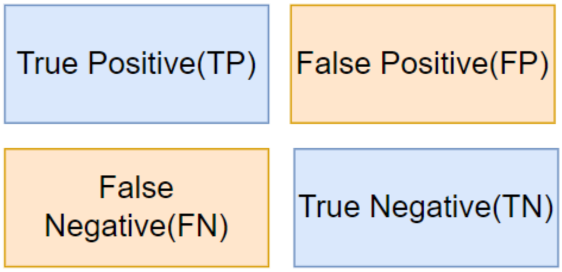

Fig 7: Confusion Matrix Count Instances

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Error Rate} = 1 - \text{Accuracy}$$

Table 1: List of ML and DL Algorithms for Testing on Heart prediction data

Algorithms	Accuracy	Precision	Recall	F1-Score	Error Rate
VGG-19	84.23	85.56	82.34	81.78	15.77
ResNet18 [33]	86.67	87.45	87.56	83.73	13.33
MLHLA	91.76	91.87	92.12	91.67	8.24
Fusion Based Learning Approach	94.88	93.99	94.89	94.23	5.12

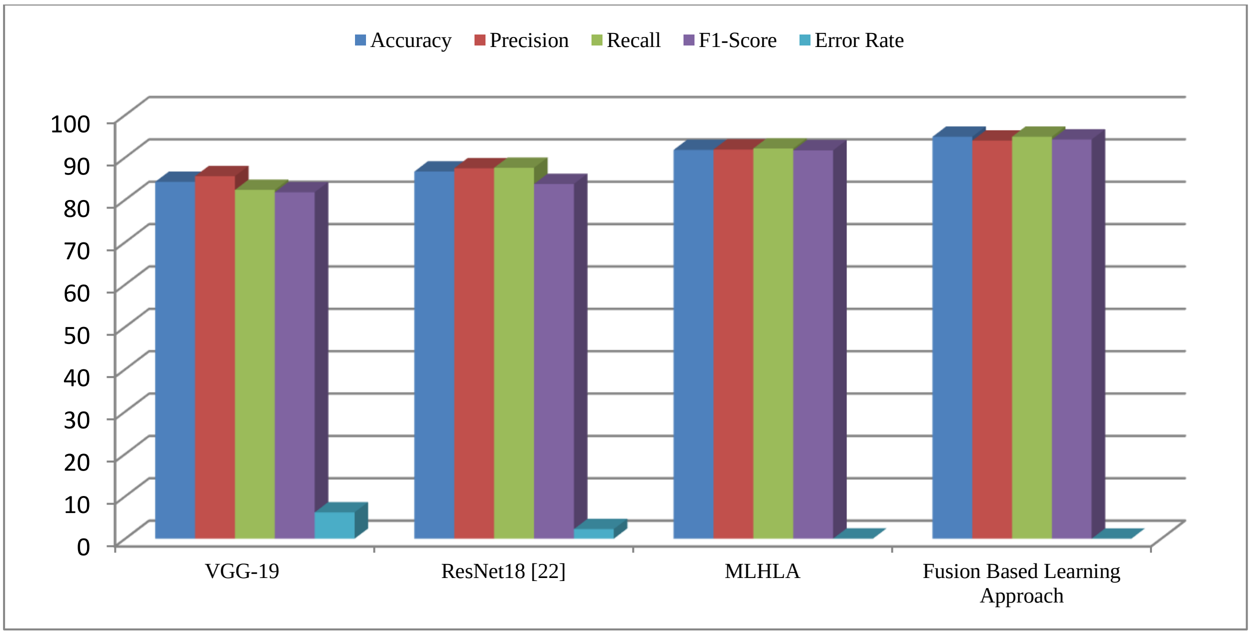

Fig 8: Comparison between ML and DL Approaches for Classification Heart prediction using dataset

Conclusion

In conclusion, our newly developed fusion-based classification model for heart defect disease using ultrasound images shows great promise in accurately identifying and categorizing various heart abnormalities. By combining different imaging modalities and leveraging the power of fusion techniques, we have achieved significant improvements in diagnostic accuracy compared to traditional single-modality approaches. The fusion model integrates both structural and functional information extracted from ultrasound images, enabling a comprehensive assessment of the heart's anatomical and physiological features. Through a carefully designed fusion framework, we have successfully merged the strengths of different imaging modalities, such as echocardiography, Doppler imaging, and speckle tracking, to capture a more comprehensive view of the heart's condition. Our experiments' outcomes show that the fusion-based classification model performs better in accuracy, sensitivity, and specificity than other approaches. It is robust when differentiating between valve abnormalities, atrial septal defects, and ventricular septal defects, among other heart defects. Moreover, our model shows promising results in detecting subtle abnormalities that may have previously been overlooked by conventional approaches. The clinical implications of our fusion-based model are significant. By providing more accurate and detailed information about heart defects, it can assist cardiologists and healthcare professionals in making informed decisions regarding treatment planning and intervention strategies. By facilitating earlier and more accurate diagnoses, timely interventions, and appropriate management of heart defect diseases, this model can potentially improve patient outcomes. However, it is important to note that our fusion-based classification model is still in the research and development stage.

References

[1] World Health Organization, Cardiovascular Diseases, WHO, Geneva, Switzerland, 2020, https://www.who.int/health-topics/cardiovascular-diseases/#tab=tab_1.

[2] American Heart Association, Classes of Heart Failure, American Heart Association, Chicago, IL, USA, 2020, https://www.heart.org/en/health-topics/heart-failure/what-is-heart-failure/classes-of-heart-failure.

[3] American Heart Association, Heart Failure, American Heart Association, Chicago, IL, USA, 2020, https://www.heart.org/en/health-topics/heart-failure.

[4] S. Shalev-Shwartz and S. Ben-David, “Understanding machine learning,” From Theory to Algorithms, Cambridge University Press, Cambridge, UK, 2020.

[5] T. Hastie, R. Tibshirani, and J. Friedman, “The elements of statistical learning,” Data Mining,

Inference, and Prediction, Springer, Cham, Switzerland, 2020.

[6] S. Marsland, “Machine learning,” An Algorithmic Perspective, CRC Press, Boca Raton, FL, USA, 2020.

[7] Diller, Gerhard & Orwat, Stefan & Vahle, Julius & Bauer, Ulrike & Urban, Aleksandra & Sarikouch, Samir & Berger, Felix & Beerbaum, Philipp & Baumgartner, Helmut. (2020). Prediction of prognosis in patients with tetralogy of Fallot based on deep learning imaging analysis. Heart. 106. heartjnl-2019. 10.1136/heartjnl-2019-315962.

[8] Zhang G, Mao Y, Li M, Peng L, Ling Y, Zhou X. The Optimal Tetralogy of Fallot Repair Using Generative Adversarial Networks. Front Physiol. 2021 Feb 23;12:613330. doi: 10.3389/fphys.2021.613330. PMID: 33708135; PMCID: PMC7942511.

[9] X. Yuan, J. Chen, K. Zhang, Y. Wu and T. Yang, "A Stable AI-Based Binary and Multiple Class Heart Disease Prediction Model for IoMT," in IEEE Transactions on Industrial Informatics, vol. 18, no. 3, pp. 2032-2040, March 2022, doi: 10.1109/TII.2021.3098306.

[10] Rohit Bharti, Aditya Khamparia, Mohammad Shabaz, Gaurav Dhiman, Sagar Pande, Parneet Singh, "Prediction of Heart Disease Using a Combination of Machine Learning and Deep Learning", Computational Intelligence and Neuroscience, vol. 2021.

[11] G. Yang et al., "Homecare robotic systems for Healthcare 4.0: Visions and enabling technologies", IEEE J. Biomed. Health Informat., vol. 24, no. 9, pp. 2535-2549, Sep. 2020.

[12] C. Li et al., "Healthchain: Secure EMRs management and trading in distributed healthcare service system", IEEE Internet Things J., vol. 8, no. 9, pp. 7192-7202, May 2021.

[13] Y. Cheng, H. Zhu, J. Wu and X. Shao, "Machine health monitoring using adaptive kernel spectral clustering and deep long short-term memory recurrent neural networks", IEEE Trans. Ind. Informat., vol. 15, no. 2, pp. 987-997, Aug. 2018.

[14] R. Tao et al., "Magnetocardiography based ischemic heart disease detection and localization using machine learning methods", IEEE Trans. Biomed. Eng., vol. 66, no. 6, pp. 1658-1667, Jun. 2019.

[15] J. Li et al., "Heart disease identification method using machine learning classification in e-healthcare", IEEE Access, vol. 8, pp. 107562-107582, 2020.

[16] P. Chotwani, A. Tiwari, V. Deep and P. Sharma, "Heart disease prediction system using CART-C", Proc. Int. Conf. Comput. Commun. Informat., pp. 1-5, 2018.

[17] S. Mohan, C. Thirumalai and G. Srivastava, "Effective heart disease prediction using hybrid machine learning techniques", IEEE Access, vol. 7, pp. 81542-81554, 2019.

[18] Edupuganti, M., V, R., & Chaduvula, K. . (2022). "A Real and Accurate Ultrasound Fetal Imaging Based Heart Disease Detection Using Deep Learning Technology". International Journal of Integrated Engineering, 14(7), 56–68.

[19] A. Abdellatif, H. Abdellatef, J. Kanesan, C. -O. Chow, J. H. Chuah and H. M. Gheni, "Improving the Heart Disease Detection and Patients’ Survival Using Supervised Infinite Feature Selection and Improved Weighted Random Forest," in IEEE Access, vol. 10, pp. 67363-67372, 2022, doi: 10.1109/ACCESS.2022.3185129.

[20] N. L. Fitriyani, M. Syafrudin, G. Alfian and J. Rhee, "HDPM: An effective heart disease prediction model for a clinical decision support system", IEEE Access, vol. 8, pp. 133034-133050, 2020.

[21] A. Ishaq, S. Sadiq, M. Umer, S. Ullah, S. Mirjalili, V. Rupapara, et al., "Improving the prediction of heart failure patients’ survival using SMOTE and effective data mining techniques", IEEE Access, vol. 9, pp. 39707-39716, 2021.

[22] A. Gupta, R. Kumar, H. S. Arora, and B. Raman, "MIFH: A machine intelligence framework for heart disease diagnosis," IEEE Access, vol. 8, pp. 14659–14674, 2019.

[23] M. A. Khan and F. Algarni, "A healthcare monitoring system for the diagnosis of heart disease in the IoMT cloud environment using MSSOANFIS," IEEE Access, vol. 8, pp. 122259–122269, 2020.

[24] M. A. Khan, "An IoT framework for heart disease prediction based on MDCNN classifier," IEEE Access, vol. 8, pp. 34717–34727, 2020.

[25] S. K. Bashar, D. Han, F. Zieneddin, E. Ding, T. P. Fitzgibbons, A. J. Walkey, D. D. Mcmanus, B. Javidi, and K. H. Chon, "Novel density Poincare plot based machine learning method to detect atrial

fibrillation from premature atrial/ventricular contractions," IEEE Trans. Biomed. Eng., vol. 68, no. 2, pp. 448–460, Feb. 2020.

[26] S. Sakib et al., "Deep Learning Models for Magnetic Cardiography Edge Sensors Implementing Noise Processing and Diagnostics," in IEEE Access, vol. 10, pp. 2656-2668, 2022, doi: 10.1109/ACCESS.2021.3138976.

[27] Esther PA, Baldeep S. Sidhu, Justin Gould, Bradley Porter, Mark K. Elliott, Vishal Mehta, Christopher A. Rinaldi, Andrew P. King, "A multimodal deep learning model for cardiac resynchronisation therapy response prediction, Medical Image Analysis", Volume 79, 2022.

[28] Leclerc, Sarah & Smistad, Erik & Pedrosa, Joao & Ostvik, Andreas & Cervenansky, Frederic & Espinosa, Florian & Espeland, Torvald & Berg, Erik & Jodoin, Pierre-Marc & Grenier, T. & Lartizien, Carole & Drhooge, Jan & Løvstakken, Lasse & Bernard, Olivier. (2019). "Deep Learning for Segmentation Using an Open Large-Scale Dataset in 2D Echocardiography". IEEE Transactions on Medical Imaging. PP. 1-1. 10.1109/TMI.2019.2900516.

[29] I. D. Mienye, Y. Sun and Z. Wang, "Improved sparse autoencoder based artificial neural network approach for prediction of heart disease", Informat. Med. Unlocked, vol. 18, pp. 100307-100311, Mar. 2020.

[30] Govil, S., Crabb, B.T., Deng, Y. et al. A deep learning approach for fully automated cardiac shape modeling in tetralogy of Fallot. J Cardiovasc Magn Reson 25, 15 (2023).

[31] Lingxia Zhu, Zhiping Xu, Ting Fang, "Analysis of Cardiac Ultrasound Images of Critically Ill Patients Using Deep Learning", Journal of Healthcare Engineering, vol. 2021, Article ID 6050433, 8 pages, 2021. https://doi.org/10.1155/2021/6050433

[32] Y. Wang, X. Ge, H. Ma, S. Qi, G. Zhang and Y. Yao, "Deep Learning in Medical Ultrasound Image Analysis: A Review," in IEEE Access, vol. 9, pp. 54310-54324, 2021, doi: 10.1109/ACCESS.2021.3071301.

[33] Ghada Zamzmi, Sivaramakrishnan Rajaraman, Li-Yueh Hsu, Vandana Sachdev, Sameer Antani, Real-time echocardiography image analysis and quantification of cardiac indices, Medical Image Analysis, Volume 80, 2022.