Detection of Valvular Heart Diseases Using Fourier Transform and Simple CNN Model

Wafaa N. Al-Sharu, Ali Mohammad Alqudah *Member, IAENG,* Shoroq Qazan, Amin Alqudah

Abstract—**In recent years, automated diagnosis of the state of health of the heart, particularly cardiac valves, has gained great success using the phonocardiogram (PCG). This work provides a low-complexity, completely automated system for diagnosing and categorizing cardiac illness based on the direct application of a multiclass Convolutional Neural Network (CNN) model, either using Softmax Classifier or KNN or SVM as a classification layer to the fast Fourier transform (FFT) of PCG signals. PCG signals are supplied into the CNN and transformed from the time domain to the frequency domain. With an analysis time of fewer than 2 seconds, the suggested technology allows us to improve performance by up to 97.66%. In the second evaluation, the methodology was evaluated on PhysioNet/Computing in Cardiology Challenge 2016 dataset achieved very high accuracy.**

Index Terms— **Sensors, Signal Processing, Phonocardiogram (PCG), Heart Valves Diseases, Fast Fourier Transform (FFT), Deep Learning**

I. INTRODUCTION

With increasing industrialization and development, cardiovascular diseases (CVDs) are becoming the most common reason for death. CVDs cause a heavy burden on human health and finances, especially in low economies. Heart sounds provide essential indicators for the condition of the human heart. Hence, they have been utilized for the early diagnosis of CVDs. This is because of their non-invasiveness and effectiveness in reflecting the mechanical motion of the heart and cardiovascular system. Cardiologists perform cardiac auscultation. It is one of the most widely used techniques to detect abnormalities in heart sounds [1]. Accurate auscultation is critical in screening patients with heart diseases. However, identification of pathological heart sounds by ear is challenging as it requires extensive clinical experience and skill and an ideal environment without ambient noise. Besides, the human ear is not sensitive to sounds within all frequency ranges [2]. Therefore, there is a need for automated heart sound analysis and classification systems that can transform heart sound signals into useful clinical informatics tools enabling the identification of different heart conditions.

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Wafaa N. Al-Sharu is a lecturer at the Department of Electrical Engineering, Hashemite University, P.O. Box 330127, Zarqa 13133, Jordan. (e-mail: wafaa.al-sharo3@hu.edu.jo).

Ali Mohammad Alqudah is a researcher at the Department of Biomedical Systems and Informatics Engineering, Yarmouk University, P.O Box 566, Irbid 21163, Jordan. (e-mail: ali_qudah@hotmail.com).

Shoroq Qazan is a researcher at the Department of Computer Engineering, Yarmouk University, P.O Box 566, Irbid 21163, Jordan. (e-mail: shoroq_qazan@hotmail.com).

Amin Alqudah is a Full Professor at the Department of Computer Engineering, Yarmouk University, P.O Box 566, Irbid 21163, Jordan. (e-mail: amin.alqudah@yu.edu.jo).

The field of research known as computer-aided diagnosis (CAD) is expanding quickly. Due to the potential for seriously misleading medical treatments caused by faults in medical diagnostic systems, research investigations have recently concentrated on enhancing computer-aided diagnosis applications. In CAD, machine learning (ML) is crucial. Diabetes, liver, dengue, hepatitis, and heart conditions are among the illnesses that ML diagnoses [3–12]. Analyzing cardiac auscultation automatically falls under the purview of signal processing. Segmentation, feature extraction, and classification are the three fundamental phases in heart sound analysis [13]. Each stage is conducted using a variety of algorithms to accurately find abnormal events and heart sounds. The goal of segmentation is to identify the basic components of each cardiac cycle, such as the first heart sound (S1), which happens during the systolic phase, and the second heart sound (S2), which happens during the diastolic period. The outcomes of segmenting heart sounds based on features using machine learning techniques have been improved. The most used segmentation method is the Hidden Markov Model (HMM) [14, 15]. Sequences of feature vectors derived from the original phonocardiogram are utilized as the HMM's observation end, and sufficient samples must be pre-labeled with the precise locations of the S1, S2, systolic, and diastolic periods at the output end to train the HMM. Heart sound segmentation using current deep learning techniques produces results with higher precision than other classification techniques [16, 17]. The goal of feature extraction is to extract distinguishing features, either for more accurate heart sound segmentation or for the step after illness categorization. According to time-dominate in, frequency-domain, and time-frequency complex domain [18], cardiac sound qualities are dependent on these three variables. Time-domain features include intervals of (S1 and S2, systolic intervals, diastolic intervals) and amplitude (mean absolute amplitude of S1 and S2 intervals). The power spectrum of each component of the heart sound across frequency bands is referred to as a frequency-domain feature [16].

The classification and detection of VHDs aim to categorize heart sounds according to distinct types of cardiac diseases. Support vector machines [19–23], neural networks [24, 25], HMMs [26], and other common classifiers are employed in the classification of heart sounds. Previous research demonstrated promising potential for detecting VHDs from heart sounds once a suitable combination of algorithms was employed for segmentation, feature extraction, and classification. Aortic regurgitation, mitral regurgitation, and pulmonary stenosis could all be distinguished by Sun's intelligent diagnostic method with accuracy rates of 98.9%, 98.4%, and 98.7%, respectively. Thompson et al. [2] used a murmur identification technique to separate pathogenic murmurs from no murmurs and harmless murmurs. 603 participants' 3180 cardiac auscultations at five different chest sites were examined. The algorithm was accurate in identifying a pathologic murmur with an accuracy of 88%, sensitivity of 93%, and specificity of 81%. Deep learning and machine learning methods have recently come to be recognized as the best methods for classifying heart sounds. According to survey studies [2, 3], deep learning-based heart sound categorization has higher accuracy than conventional machine learning. To distinguish between normal and pathological heart sounds, Milani et al. [27] employed Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) techniques. After using LDA to lower the dimensionality of the retrieved features, a single-layer ANN model was utilized to classify the normal and abnormal PCG signals. The findings demonstrated that frequency-domain features alone do not consistently outperform time-domain features in categorization. When time and frequency domain information was integrated, the LDA/ANN technique achieved the highest classification accuracy (93.3%). To categorize heart illness, Nahar et al. [28] employed straightforward machine learning techniques such as Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Naive Bays (NB). Multiple cardiac sound signal features, including MFCC, Delta MFCC, FBANK, and a combination of MFCC and FBANK features, were subjected to the ML models' execution. The built-in ML model demonstrates that the combination of MFCC and FBANK characteristics, which was not previously used in the literature, led to the best accuracy of 99.2%. To identify cardiac disorders, Arora et al. [29] used digital Phonocardiogram (PCG) data categorized as heart sounds. They combined XGBoost with meta-heuristic algorithms like genetic algorithm and ant colony optimization for hyper-parameter tuning. Heart sounds were correctly classified by the XGBoost 92.8% of the time. Additionally, the classification accuracy of XGBoost beat DT (85.5%), RF (90.6%), and Adaboost when the authors compared it to other approaches (82.5%). To diagnose valve heart illness from unsegmented phonocardiogram (PCG) signals, Khan et al. [30] utilized a variety of methods, including cartesian genetic programming evolved artificial neural network (CGPANN), artificial neural network (ANN), and Support Vector Machine (SVM). The various algorithms were trained using time- and frequency-domain characteristics that were taken from PCG signals that were not segmented. SVM fared better than other techniques, with a 73%accuracy rate. Cardiologists are trained to interpret heart sounds, and Tanmay et al. [31] employed Wavelet Transform (WT) to extract wavelet properties from the heart sounds. They performed a two-step classification of heart sound quality followed by a classification of heart pathology using bagging and boosting trees, logistic classifiers, and SVM (i.e., normal, or abnormal). Bagging trees were shown to be the most efficient classification algorithm for the first stage, which comprised the signal quality classification task. Based on its greatest validation accuracy, the boosted trees classifier utilising Logistic Boost was chosen for classification in the second step, which included the task of classifying cardiac abnormalities (77%). As we shall see, numerous research papers have discussed the use of deep learning and machine learning (supervised and unsupervised) algorithms in the identification and prognosis of valvular heart disorders. The majority of these publications treat the machine learning and deep learning algorithms like a black box without making any attempts to enhance them. This is a significant barrier for the healthcare industry, which calls for more adaptable, well-understood behaviors, and comprehensible models. The challenge of creating interpretable machine learning models is catching up and remains unsolved. In order to identify heart sounds to detect heart valve disorders utilizing Fourier transform inputs, this study will present a deep learning CNN model.

II. Methodology

This research study aims to present a novel methodology based on transforming PCG signals into frequency representation using FFT that can be utilized to categorize heart sounds in both binary and multi-class classification scenarios. Figure 1 depicts the suggested methodology's Block diagram. The following subsections are covered in length in this section: the dataset utilized, the suggested approach, the classifier, and the performance evaluation.

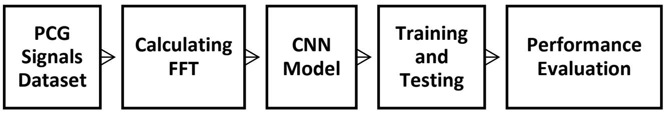

Fig. 1. Block Diagram of the Proposed Model.

A. Materials

In this study, one dataset was used, which is from Yaseen et al. [32]. This dataset has five classes of normal and four heart murmurs. All files in the dataset are stored in wav format, with a sampling rate of 8000 Hz. The samples in this dataset have been resized to have 24,000 samples. The dataset utilized in this study is summarized in Table 1. Figure 2 shows a sample signal from the used datasets.

TABLE I
MULTI CLASSES DATASET INFORMATION.

Dataset	Training samples	Testing samples	Total Samples
Multiclass Dataset	700	300	1000

B. Methods

1. Fast Fourier Transform (FFT)

The discrete Fourier transform (DFT) or inverse of a signal is calculated using a fast Fourier transform (FFT) (IDFT). When using Fourier analysis, a signal is converted from its original domain, which is often time or space, to a representation in the frequency domain, and vice versa. The DFT [33] is produced by breaking down a set of numbers into components with different frequencies.

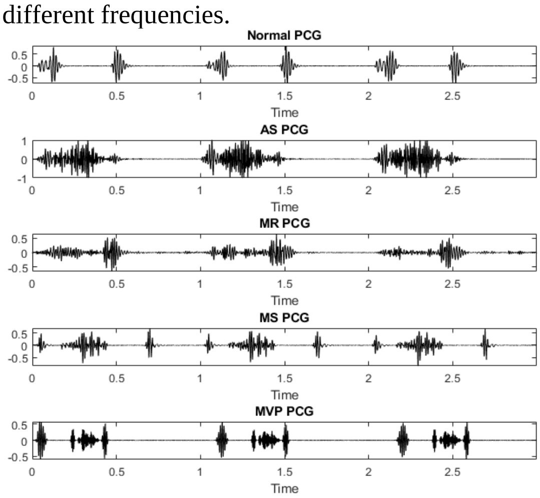

Fig. 2. Block Diagram of the Proposed Model.

Although it is useful in many fields, this process is frequently too slow to compute directly from the definition. An FFT can swiftly conduct such adjustments by splitting the DFT matrix into a product of sparse (zero) elements. It succeeds in making the DFT computation less difficult as a result [34]. Particularly for sizable data sets with N in the hundreds of millions, the performance disparity can be significant. In the presence of round-off error, several FFT methods are more accurate than directly or indirectly evaluating the DFT specification. Several published theories, including group theory, number theory, and simple complex-number arithmetic, constitute the foundations for several FFT algorithms [35]. The fields of mathematics, physics, engineering, and music frequently make use of fast Fourier transformations. While the basic ideas gained popularity around 1965, several algorithms were created as early as 1805. The FFT was referred to as "the most important numerical algorithm of our lifetime" by Gilbert Strang in 1994, and it was listed as one of the Top 10 Algorithms of the 20th Century by the IEEE Journals Computing in Science & Engineering [36]. Because the majority of the frequency components fall within this frequency range, the Fourier transform of signals in this study was trimmed to only include 350 Hz from the 4000 Hz spectrum [37]. Figure 3 displays all four signal types in their entirety.

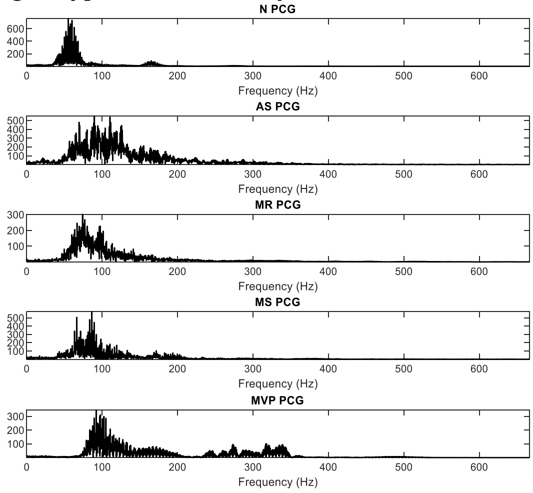

Fig. 3. Frequency Content of Different PCG Signals.

As a result, the frequency content fed to the CNN model will be clipped only to 350 Hz (1000 Samples). Figure 4 shows the frequency content of different PCG signals with limited to only 350 Hz [37, 38].

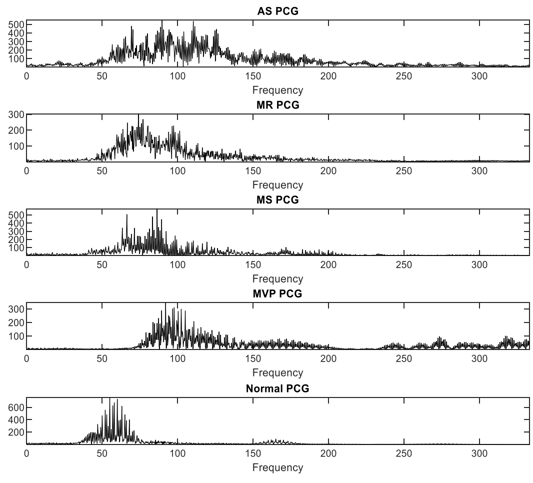

Fig. 4. Frequency Content of Different PCG Signals Limited to 350 Hz.

2. CNN Model

Due to the increasing availability of massive datasets, deep learning is one of the most recent and cutting-edge artificial intelligence techniques [39]. In order to achieve successive phases of input processing, deep learning develops a distinctive architecture made up of numerous sequential layers [1, 6, 12–14]. The deep structure of the human brain serves as both an inspiration for and a model for deep learning [40]. Since the human brain has a complex internal structure with many hidden layers, we can extract and abstract deep features at different levels and from different perspectives. Several deep learning algorithms have recently been introduced [40]. CNN [39, 40] (Convolutional Neural Network). Input, convolution, RELU, totally connected, classification, and output are just a few of the numerous layers that make up CNN. These layers build a CNN model that can perform the required function. In a number of scientific disciplines, CNN has excelled, particularly in the medical sector [39]. The main purpose of CNN layers is to extract comprehensive, representative, and discriminative properties. Downsampling, feature selection, and pattern classification will all be done in the earlier layers [40]. In the suggested methodology, we divided the input ECG beats into six groups using a CNN model. Eight layers make up the model. The proposed CNN model has fewer layers than earlier CNN models used in the literature. It is more suitable for embedded systems due to the decreased number of layers because it requires less time and resources to run and train the model and identify the class of newly input PCG FFT. The proposed CNN design is shown in Figure 5.

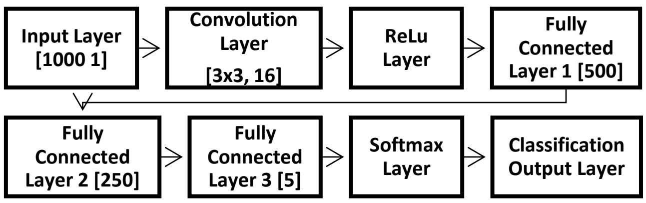

Fig. 5. The overall framework of CNN-based beat classification model.

3. Hybrid CNN-ML Classifier

In this work, the CNN's fully connected layer—which comes before the Softmax layer, which is used for classification—was used as a feature extraction layer. A feature vector with five features, each of which represents a different sort of class, will be the output of the entirely connected layer [39]. When the used CNN is properly constructed and trained on a sizable dataset, the features can extract representative features for the input data [39]. MxN is the dimension of the retrieved features used in this study, where M is the number of photos and N is the number of classes (in our instance, five) [39].

a. KNN Classifier

The main objective of the K-means clustering method is to divide data with M points and N dimensions into K clusters while minimizing the sum of squares within each cluster. The main idea of the clustering algorithm is to define k centers, one for each cluster. These K-centers should be strategically placed because different settings yield varying effects. The next step is to link each point in a given data set with the closest center by using the least sum of squares against all centers [37, 38].

b. SVM Classifier

A well-known and widely used supervised machine learning method called the Support Vector Machine (SVM) is used largely to categorize data into two groups. By determining the optimal hyperplane between the datasets, the SVM method uses the input training data to build a model that predicts the new sample class. This hyperplane must maximize the distance between the closest data point and the separation hyperplane. In particular in Biomedical Engineering, the SVM has been successfully used for a variety of real-world applications, such as face identification, recognition, and verification, image retrieval, handwritten character, and digit recognition [38].

4. Performance Evaluation

The confusion matrix for both binary and multi-class scenarios was generated, followed by a comparison of the classifier outputs with the corresponding original label of the heart sound, in order to assess the performance of the proposed methodology in classifying heart sounds using instantaneous frequency features [40]. The generated confusion matrices are used to calculate accuracy, sensitivity, and specificity, and these values are used as a metric to judge how precisely the classifier categorizes heart sounds. The Equations below contain the formulas for accuracy, sensitivity, specificity, and precision.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{1}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{T\text{N+FP}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{T\text{P+FP}} \tag{4}$$

The false positive rate (FPR) and true positive rate (TPR), with values ranging from 0 to 1, were given as the X and Y axes of a receiver operating characteristic (ROC) curve that was created to illustrate the performance of the LSTM model. The sensitivity equation was used to determine the TPR values, whereas the FPR was determined by deducting the specificity value from 1. When the ROC curve was more closely positioned to the upper left corner, the model performed better. Although the ROC's area under the curve (AUC) was also used, the accuracy of the model's predictions increased with increasing AUC values [38, 37, 39, 40].

III. RESULTS

In this part, the effectiveness of the suggested technique is evaluated. We compare all of the models that have been offered before deciding which model is the best. All models in this experiment are run on a computer with 16GB of RAM and an Intel(R) Core-I5 CPU clocked at 2.3GHz. Using adaptive moment estimation, we maximize backpropagation using a 150-batch size, a 0.001 learning rate, and several 30-epoch iterations.

1. CNN Model Results

In this section the result of the CNN model, Figure 6 shows the accuracy and loss results of the training during the model training. While Figure 7 shows the confusion matrix of the testing data using the CNN model. Finally, Figure 8 shows the ROC curve.

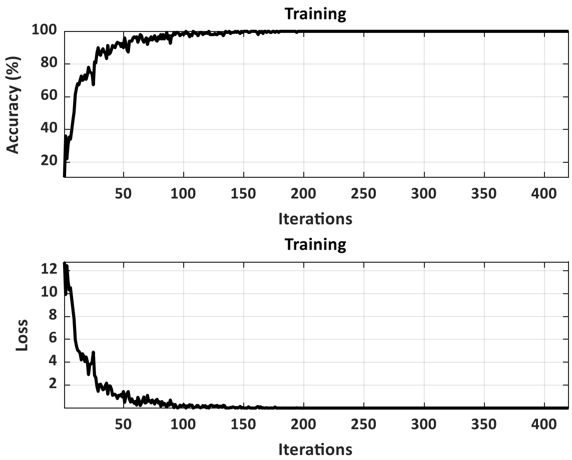

Fig. 6. The Training Accuracy and Loss using Proposed CNN Model.

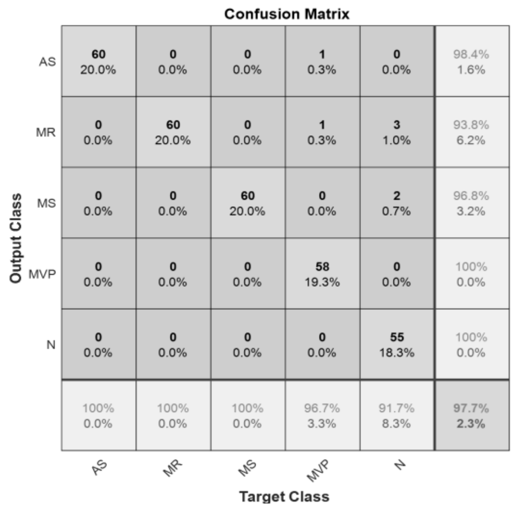

Fig. 7. Confusion Matrix of Testing Dataset using Proposed CNN Model.

To summarize the results of the previous figures, Table 2 shows the performance of different classes and the overall performance using the proposed methodology.

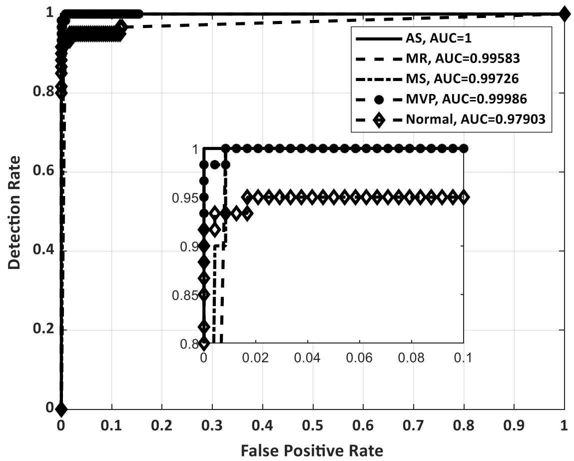

Fig. 8. ROC Curve of Using Proposed CNN Model.

2. CNN-SVM Model Results

In this section the result of the CNN-SVM model, Figure 9 shows the confusion matrix of the training data using the CNN-SVM model. While Figure 10 shows the confusion matrix of the testing data using the CNN-SVM model. Finally, Figure 11 shows the ROC curve.

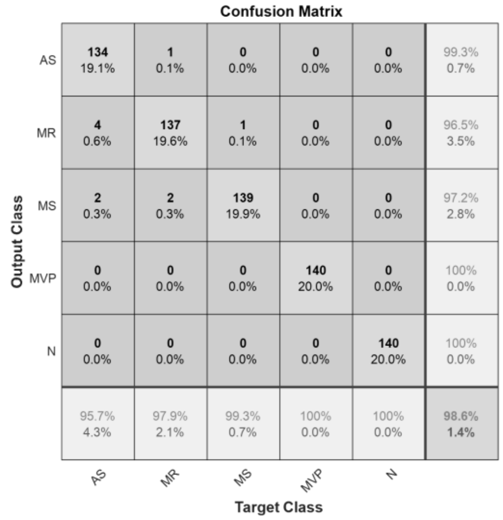

Fig. 9. Confusion Matrix of Training Dataset using Proposed CNN-SVM Model.

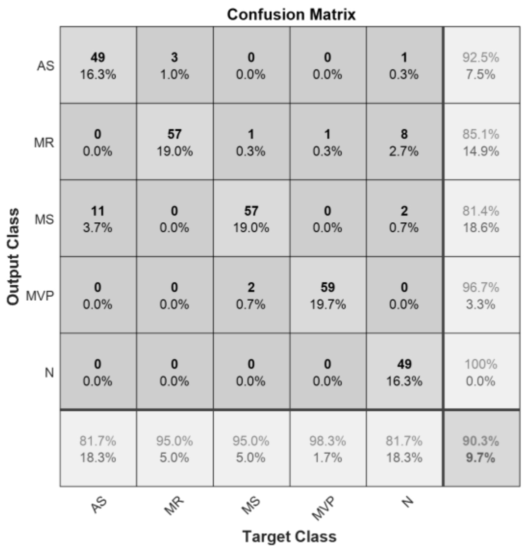

Fig. 10. Confusion Matrix of Testing Dataset using Proposed CNN-SVM Model.

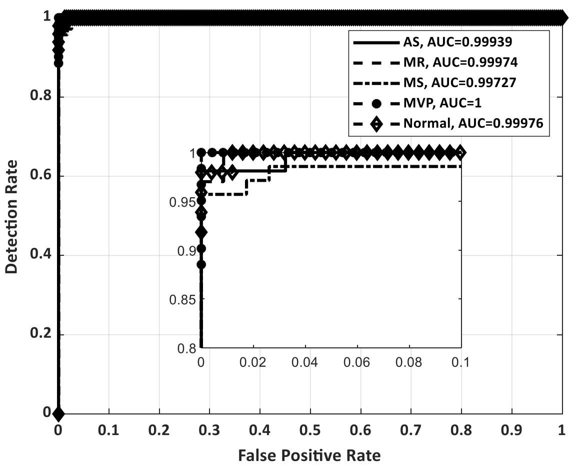

Fig. 11. ROC Curve of Using Proposed CNN-SVM Model.

3. *CNN-KNN Model Results*

In this section the result of the CNN-KNN model, Figure 12 shows the confusion matrix of the training data using the CNN-KNN model. While Figure 13 shows the confusion matrix of the testing data using the CNN-KNN model. Finally, Figure 14 shows the ROC curve.

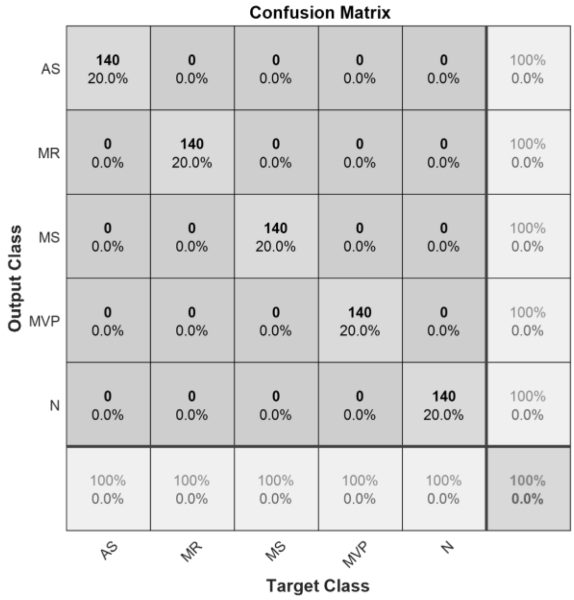

Fig. 12. Confusion Matrix of Testing Dataset using Proposed CNN-KNN Model.

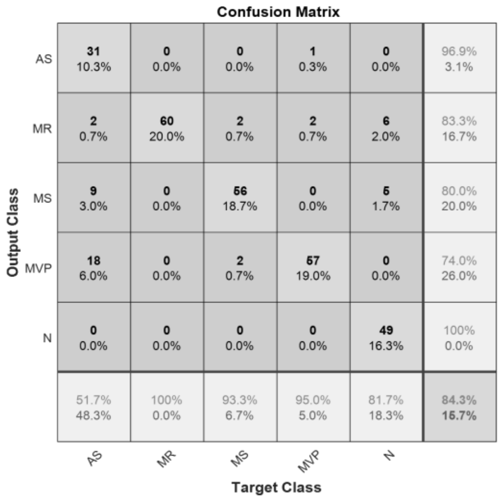

Fig. 13. Confusion Matrix of Testing Dataset using Proposed CNN-KNN Model.

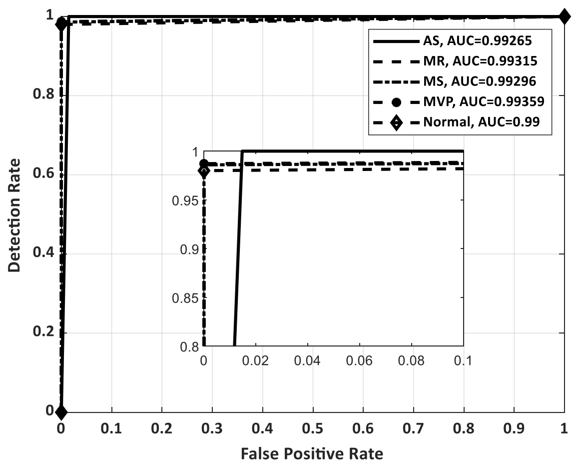

Fig. 14. ROC Curve of Using Proposed CNN-KNN Model.

4. *PhysioNet/Computing in Cardiology Challenge 2016 Dataset Results*

As a second assessment of the suggested technique and CNN model robustness, the results of applying the proposed CNN model to the PhysioNet/Computing in Cardiology Challenge 2016 Dataset are shown in this section. One of the biggest and most popular datasets for analyzing heart sound classification issues is the PhysioNet/Computing in Cardiology Challenge 2016 Dataset [38]. Figure 15 displays the accuracy and loss outcomes of the model training. The confusion matrix of the training and testing data, respectively, using the CNN model is shown in Figures 16 and 17. Lastly, the ROC curve is displayed in Figure 18.

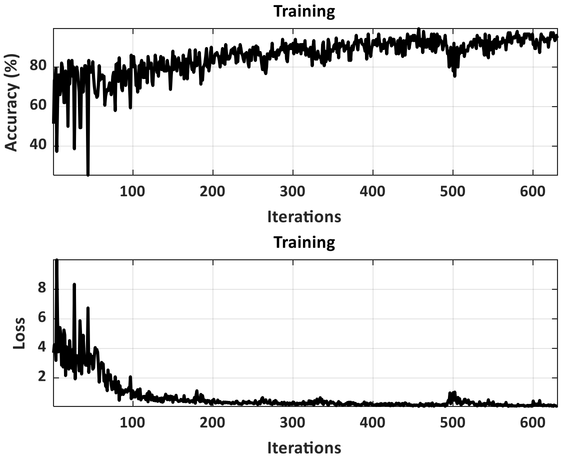

Fig. 15. The Training Accuracy and Loss using Proposed CNN Model on the Binary Dataset.

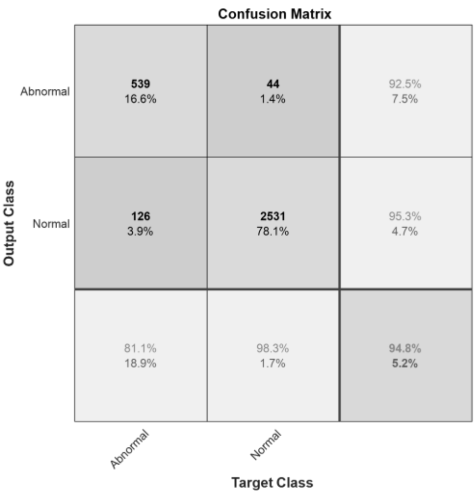

Fig. 16. Confusion Matrix of Training Dataset using Proposed CNN Model on the Binary Dataset.

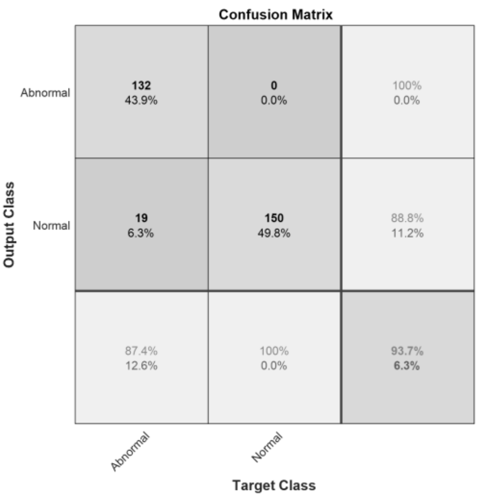

Fig. 17. Confusion Matrix of Testing Dataset using Proposed CNN Model on the Binary Dataset.

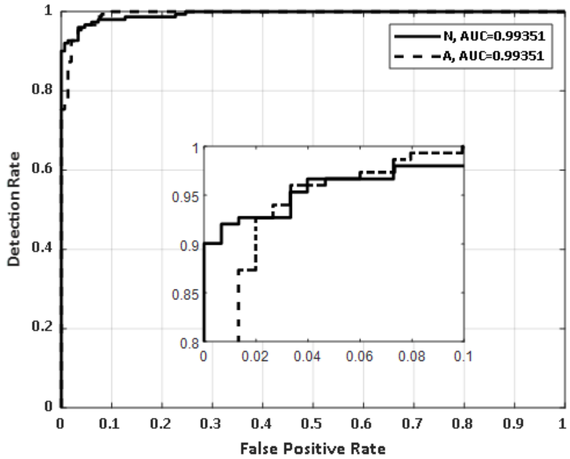

Fig. 18. ROC Curve of Using Proposed CNN Model on the Binary Dataset.

additionally, to conduct a thorough comparison for the second dataset, the hybrid CNN-KNN and CNN-SVM techniques have been used. The CNN-SVM model's output is shown in the following figures. Figure 19 displays the confusion matrix created from the training set of data. Figure 20 displays the confusion matrix created by the CNN-SVM model using the testing data. Lastly, the ROC curve is displayed in Figure 21.

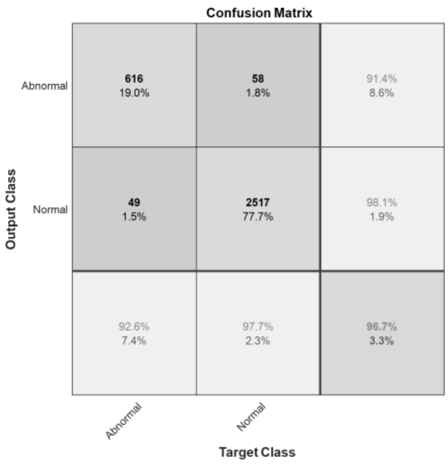

Fig. 19. Confusion Matrix of Training Dataset using Proposed CNN-SVM Model on the Binary Dataset.

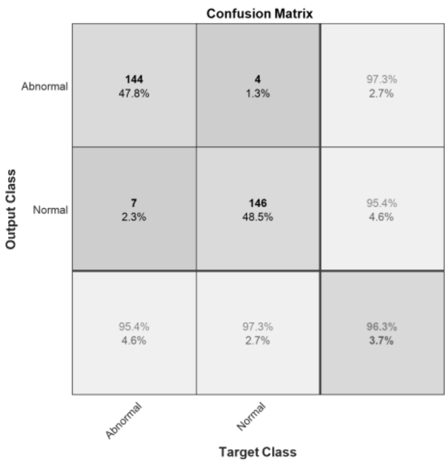

Fig. 20. Confusion Matrix of Testing Dataset using Proposed CNN-SVM Model on the Binary Dataset.

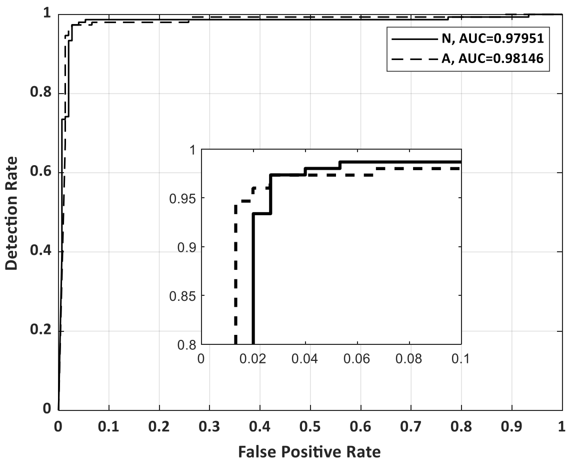

Fig. 21. ROC Curve of Using Proposed CNN-SVM Model on the Binary Dataset.

The following figures show the result of the CNN-KNN model, Figure 22 shows the confusion matrix of the training data using the CNN-KNN model. While Figure 23 shows the confusion matrix of the testing data using the CNN- KNN model. Finally, Figure 24 shows the ROC curve.

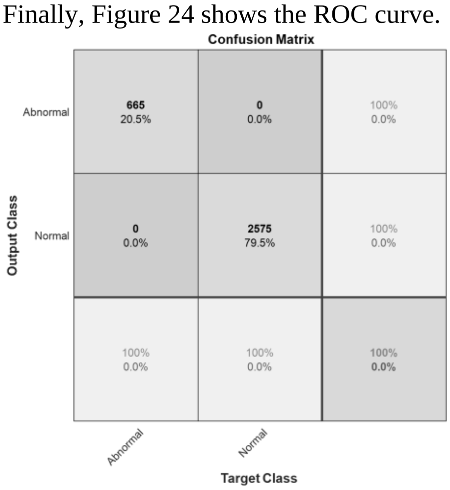

Fig. 22. Confusion Matrix of Training Dataset using Proposed CNN-KNN Model on the Binary Dataset.

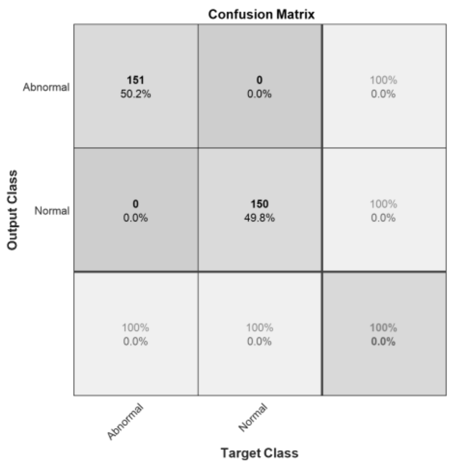

Fig. 23. Confusion Matrix of Testing Dataset using Proposed CNN- KNN Model on the Binary Dataset.

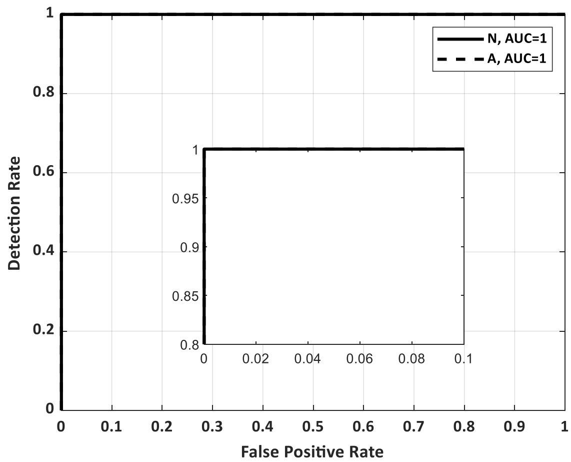

Fig. 24. ROC Curve of Using Proposed CNN- KNN Model on the Binary Dataset.

IV. DISCUSSION

The goal of the proposed study is to ascertain the effects of automatically extracting features from signals' frequency content using a deep learning model on the categorization of heart sound signals for multiclass heart valve situations. Our research primarily examined how the Fourier transform-based deep learning model affected the categorization accuracy of heart sounds. Our solution outperforms other methods that are currently available in the literature in the heart sound classification scheme in terms of automated classifier results.

TABLE II
THE CLASSIFICATION REPORT OF THE PROPOSED CNN MODEL USING TESTING SET.

Class	Accuracy %	Sensitivity %	Specificity %	Precision %	AUC
AS	100	100	99.58	98.36	1.0
MR	100	100	98.33	93.75	0.99
MS	100	100	99.17	96.77	0.99
MVP	96.66	96.66	100.00	100.00	0.99
Normal	91.66	91.66	100.00	100.00	0.97
Overall	97.66	97.66	99.42	97.77	0.99

TABLE III
THE CLASSIFICATION REPORT OF THE PROPOSED CNN-SVM MODEL USING TESTING SET.

Class	Accuracy %	Sensitivity %	Specificity %	Precision %	AUC
AS	78.33	78.33	99.58	97.92	1.0
MR	100	100	95.83	85.72	0.99
MS	93.33	93.33	93.33	77.78	0.99
MVP	96.67	96.67	98.75	95.09	1.0
Normal	81.67	81.67	100	100	0.99
Overall	90.00	90.00	97.50	91.30	0.99

TABLE IV
THE CLASSIFICATION REPORT OF THE PROPOSED CNN-KNN MODEL USING TESTING SET.

Class	Accuracy %	Sensitivity %	Specificity %	Precision %	AUC
AS	51.67	51.67	99.58	96.88	0.99
MR	100	100	95	83.33	0.99
MS	93.33	93.33	94.17	80	0.99
MVP	95	95	91.67	74.03	0.99
Normal	81.67	81.67	100	100	0.99
Overall	84.33	84.33	96.08	86.85	0.99

Most of the research in the literature focus on using the binary dataset (PhysioNet/Computing in Cardiology Challenge 2016 Dataset) to evaluate their proposed methodologies. We have already used this dataset as a secondary source of evaluation. Table V shows a summary of the testing of the proposed methodology on the PhysioNet/Computing in Cardiology Challenge 2016 Dataset.

TABLE V
THE CLASSIFICATION REPORT OF THE PROPOSED MODELS USING TESTING SET OF BINARY DATASETS.

Class	Accuracy %	Sensitivity %	Specificity %	Precision %	AUC
CNN	93.69	87.42	100	100	0.9935
CNN-SVM	96.35	95.36	97.33	97.30	0.9805
CNN-KNN	100	100	100	100	1.0

Table VI displays a comparison of the suggested methodology's findings with those of other recent techniques in the literature. Both of the free online datasets (PhysioNet CinC Challenge 2016 Dataset and Pascal Dataset) or their records were used in the majority of the studies listed and compared in Table VI. They employ a varied number of classes, records, and characteristics, which is obvious. These elements have a big impact on how well the various classification techniques work. However, more than 90% of the approaches reported in the literature have attained high recognition rates.

TABLE VI
COMPARING BETWEEN PROPOSED METHODOLOGY AND METHODS IN LITERATURE.

Reference	Methodology	Number of Classes	Accuracy %
[2]	CAD System	2	88
[19]	ANN	2	98.9
[27]	LDA/ANN	4	93.3
[28]	ANN	2	99.2
[29]	XGBoost	2	92.8
[30]	SVM	2	73
[31]	Logistic Boost	2	77
Proposed 5 Classes	CNN-KNN	5	84.33
	CNN-SVM	5	90.00
	CNN Model	**5**	**97.66**
Proposed 2 Classes	**CNN-KNN**	2	**100**
	CNN-SVM	2	96.35
	CNN Model	2	93.69

Table VI shows that all literature studies focused on machine learning techniques, but none did so for deep learning. While time domain-based deep learning models contain the time difference between the two primary components of the heart sound signal (S1 and S2), the extracted Fourier transform generally concentrated on the frequency domain. The suggested system demonstrates that the newly developed way of feeding Fourier transform data to deep learning models rather than time-domain signals offers greater classification rates when compared to existing methods. A desktop computer with an Intel Core i5-6700 processor running at 2.4 GHz and 12 GB of RAM is used to test the system's time consumption in order to determine its real-time performance. The system demonstrates that an average of 244.71382 mS and 9.71287 mS, respectively, are needed to calculate the Fourier transform for each PCG signal once the signal has been loaded. The duration of the Fourier transforms and classification is shown in Table VII.

TABLE VII
AVERAGE CONSUMPTION TIME FOR PROPOSED METHODOLOGY.

Process	Average Time (ms)	Total Time (ms)
FFT	244.71382	
Classification		
Softmax	9.71287	254.42669
KNN	20.54881	265.26263
SVM	25.22153	269.93535

V. CONCLUSION

In this study, we successfully proposed a very light and quick deep learning model based on one-dimensional CNN with fast Fourier transform (FFT) for automated diagnosis of heart valve dysfunction. With the CNN model, the model achieved an overall accuracy of 97.66% on five classes from the PCG signals dataset, and with the CNN-KNN model, it achieved 100% accuracy for the PhysioNet/Computing in Cardiology Challenge 2016 dataset. The study's suggested converting strategy and model are simple and suitable for embedded system applications. At the same time, our method performs better than cutting-edge networks. The results demonstrate that the suggested network architecture is effective in obtaining deep features from PCG signal FFTs. By employing a bigger dataset and a larger convolution layer kernel, the test accuracy can be improved. An effective model with a few parameters makes up our network.

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Wafaa Al-Sharu received her MSc from Jordan University of Science & Technology in 2008 and BSc from Mutah University in 2001. Her research areas are in the field of Signal Processing and Analysis and Artificial Intelligence. Currently, she is working at the Department of Electrical Engineering, Hashemite University, Zarqa, Jordan. She has extensive experience in teaching electrical engineering courses like signals and systems, electrical circuits, electrical machines, and electromagnetic and communication systems in different universities in Jordan like Jordan University of Science & Technology, Yarmouk University, and AlBalqa Applied University. She also served on different scientific committees at the Department of Electrical Engineering, Hashemite University, Zarqa, Jordan, and the Department of Telecommunication Engineering, Yarmouk University, Irbid, Jordan.

Ali Mohammad Alqudah, MSc received his B.Sc. and M.Sc. both from Yarmouk University in 2015 and 2018 respectively. His research area is in the field of Biomedical Signal Processing, Image Processing and Analysis, Deep Learning, and Machine Learning. Alqudah has published high-quality research articles in journals and conferences. In 2021, he was listed on Stanford's list of the top 2% scientists in the world. Ali serves as a reviewer for several peer-reviewed journals. Currently, he is working towards his Ph.D. and working as Graduate Research Assistant and Ph.D. student at the Biomedical Engineering Program, University of Manitoba, Winnipeg, Canada.

Shoroq Qazan, MSc received her B.Sc. and M.Sc. both from Yarmouk University in 2017 and 2022 respectively. Her research area is in the field of Biomedical Signal and Image Processing, Deep Learning, Machine Learning, and Brain Signal Processing. She published several high-quality research articles.

Amin Alqudah received his M.Sc. and Ph.D. in Electrical Engineering from the University of Colorado, USA in 2005, and from Colorado State University, USA in 2009, respectively. He received his bachelor's degree in communications engineering from Yarmouk University, Jordan in 1999. Since 2009, he has been working with the Department of Computer Engineering, Hijjawi Faculty for Engineering Technology, Yarmouk University, Jordan. His research interests include Image Processing, Neural Networks, Machine Learning, and adaptive signal processing.