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RESEARCH ARTICLE

Deep Learning-Based Feature Engineering to Detect Anterior and Inferior Myocardial Infarction Using UWB Radar Data

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ABSTRACT Cardiovascular disease is the main cause of death worldwide. The World Health Organization (WHO) reports that 17.9 million individuals die yearly due to complications from heart disease and other heart-related ailments. ECG monitoring and early detection are critical to decreasing myocardial infarction (MI) mortality. Thus, a non-invasive method to accurately classify different types of MI would be extremely beneficial. Our proposed study aims to detect and classify Anterior and Inferior MI infarction with advanced deep and machine learning techniques. A newly created UWB radar signal-based image dataset is used to conduct our study experiments. A novel Convolutional spatial Feature Engineering (CSFE) technique is proposed to extract the spatial features from the image dataset. The spatial features consist of both spatial and temporal information which allows machine learning models to leverage both the spatial and temporal relationships present in the data. Study results show that using the proposed CSFE technique, the advanced machine learning techniques achieved high-performance accuracy scores. The K-Neighbors Classifier (KNC) outperformed with a high-performance accuracy score of 98% for detecting Anterior and Inferior patients. The applied methods are fully hyperparametric tuned, and performance is validated using the k-fold cross-validation method.

INDEX TERMS Cardiovascular disease, anterior and inferior, MI infarction, UWB radar, machine learning, transfer learning.

I. INTRODUCTION

Cardiovascular disease (CVD) is a major public health concern worldwide, responsible for a significant proportion of global mortality [1]. According to the World Health Organization (WHO), CVD accounts for 31% of global deaths, with an estimated 17.9 million people dying each year due to heart-related complications, including heart disease [2]. Low- and middle-income countries are disproportionately affected, with more than three-quarters of all CVD fatalities occurring in these regions [2]. Heart attacks and strokes are the leading causes of CVD-related deaths, accounting for more than four out of every five fatalities [1]. Several modifiable risk factors contribute to the development of CVD, including an unhealthy diet, lack of physical activity, alcohol and cigarette use, and hypertension [2]. Myocardial infarction (MI), also known as a heart attack, is a severe form of CVD and is one of the leading causes of mortality worldwide [3]. Every year, over 8 million people die due to MI [2]. MI occurs due to the acute thrombotic blockage of a coronary artery

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at the site of atherosclerotic disease, leading to the destruction of heart muscle tissue [3]. Clinical symptoms of MI include chest pain and shortness of breath [4]. However, these symptoms and physical markers are neither sensitive nor specific for MI diagnosis [5]. MI can occur in various areas of the heart, including the Inferior, Anterior, septal, posterior, lateral, Inferior-lateral, septal-anterior, and posterior-lateral regions [5], [6]. It causes cardiac tissue damage due to a lack of oxygen and nutrients [6]. The authors decided to focus on the examination of Anterior and Inferior MI owing to their comparatively higher incidence rates. One study [7] found that about 40% of all MI occur in the inferior wall, whereas [8], [9] reported that about 33% of all MI instances occur in the anterior wall.

Anterior MI is distinguished by the occurrence of damage to the myocardium within the (front) Anterior region of the heart, specifically affecting the Anterior wall of the left ventricle [10]. The area receives vascular perfusion from the left anterior descending (LAD) artery, a branch of the left coronary artery. The manifestation of an Anterior MI may arise due to the obstruction or occlusion of the LAD coronary artery [10]. The left ventricle, which is the largest and most robust chamber of the heart, plays a crucial role in the circulation of oxygenated blood throughout the body. The contractile function of the left ventricle experiences notable impairment due to an Anterior MI [11], [12]. The diminished contractile function of the left ventricle can lead to a decrease in cardiac output, which is characterized by a reduction in the heart's ability to efficiently circulate blood [13]. Conversely, an Inferior MI is distinguished by the damage of the myocardial tissue, specifically affecting the lower (Inferior) region of the heart [14], [15]. The primary supplier of blood to this particular area is the right coronary artery (RCA), occasionally supplemented by the left circumflex artery (LCx) [15]. The presence of an Inferior MI can have adverse consequences on both the right ventricle and the Inferior region of the left ventricle [14]. The contraction of the right ventricle is responsible for facilitating the transportation of deoxygenated blood to the lungs, where it undergoes the process of oxygenation. According to the studies conducted by Jern et al. [16] and Burns and Buttner [10], it has been observed that individuals diagnosed with Anterior MI exhibit a reduced ejection fraction in comparison to those with Inferior MI. The ejection fraction is a quantitative assessment of cardiac performance, specifically evaluating the efficiency with which the heart expels blood during each contraction. According to Jern et al., [16], a reduced ejection fraction indicates impaired cardiac pumping function, potentially resulting in the development of heart failure.

Early identification and diagnosis of MI are critical factors in reducing mortality rates associated with the condition. Currently, electrocardiogram (ECG) monitoring is one of the most commonly used diagnostic methods for detecting MI. However, ECG readings can be complicated and time-consuming to interpret, and the use of ECG electrodes may cause skin irritation and allergies [17], [18], [19]. Moreover, the time-varying dynamics and morphological properties of a single-lead ECG signal can exhibit significant differences among individuals with MI, depending on the region of MI and the degree of myocardial damage [4]. To address these issues, a non-contact approach to accurately classify different forms of MI is required. Ultrawideband (UWB) radar is emerging as a potential non-contact approach for vital sign monitoring and diagnosis [19], [20], [21], [22], [23], [24]. UWB transmissions can generate high-bandwidth signals using very short-duration pulses and can detect and monitor micro-movements and vibrations like breathing and heartbeats [25]. Infrared-UWB (IR-UWB) radar, in particular, has several advantages, such as low emission power, the ability to penetrate various materials and barriers, and the absence of privacy concerns related to visible light or skin color [23], [25]. The non-intrusive nature of IR-UWB radar and its ability to operate in various settings make it a promising tool for MI diagnosis.

The scientific research contributions of our proposed study related to detecting and classifying Anterior and Inferior MI infarction are followed as:

- A new dataset is collected, which is based on a total of 858 observations, from Anterior and Inferior MI patients. The dataset is collected from real patients at Sheikh Zayed Medical College and Hospital (SZMC&H), Rahim yar khan, Pakistan, under the supervision of a resident cardiologist.
- A novel CSFE feature engineering technique is proposed to extract the spatial features from the collected IR-UWB radar-based image dataset. CSFE features are extracted from greyscale images, and a new feature set is formed along with the target labels. Study results show that using the proposed CSFE technique, the applied methods achieved high-performance scores.
- An advanced neural network and five machine learning techniques are applied in comparison to evaluate performance. The hyperparameters optimization and k-fold cross-validation techniques are employed to validate the performance scores of each applied method. The computation complexity analysis is also performed to assess the efficiency of the proposed approach for detecting the detect Anterior and Inferior MI infarction.

The rest of the article is organized as follows. Section II comprises a literature review, section III describes methodology and experiments while results are described in section IV. The discussion and conclusion are presented in sections VI.

II. LITERATURE REVIEW

Myocardial infarction (MI) is a major cause of mortality and morbidity worldwide, with the highest risk of death occurring in the first few hours after onset. Therefore, early detection of myocardial ischemia is crucial for the effective management and screening of MI patients. However, various studies have found that the initial diagnosis of patients with chest pain often leads to inappropriate admissions of patients who do not have MI, and vice versa. In order to achieve early diagnosis, a combination of physical examination, precise electrocardiogram findings, assessment of cardiac troponins, and patient history are critical.

To aid in the diagnosis of MI, researchers have developed various systems to detect different types of MI. One such system is an 11-layer deep convolutional neural network (CNN) developed by [26] for automated diagnosis of MI. The CNN utilized electrocardiogram (ECG) signals from the publicly accessible Physikalisch-Technische Bun-desanstalt (PTB) dataset, and applied noise reduction and baseline wander removal using the Daubechies wavelet 6 mother wavelet function. The Pan Tompkins technique was then used to identify R-Peaks. The CNN achieved accuracy rates, sensitivities, and specificities of 93.53%, 93.71%, and 92.83% for noisy ECG signals, and average accuracy, sensitivity, and specificity of 95.22%, 95.49%, and 94.19% for noise-free ECG signals. The study [27] proposed a method for MI diagnosis using harmonic phase distribution patterns in ECG data. Two unique features reflecting variations in the ECG waveform's morphology and timing were detected for each of the three conventional ECG leads. Logistic regression (LR) and a threshold-based classification method were applied to distinguish between normal and MI subjects. The suggested method has successfully identified various forms of MI data with high accuracy rates.

A multi-lead attention mechanism (MLA-CNN-BiGRU) framework for detecting MI using 12-lead ECG signals from the PTB database was proposed in [28]. Intra-patient and inter-patient accuracy rates for the model are 99.93% and 96.5%, respectively. DCNN and Gabor-filter DCNN models were by study [29] compared to classify four cardiovascular disease subtypes: normal, CAD, MI, and CHF. The Gabor-filter DCNN model outperformed the DCNN model, achieving 99.55 percent accuracy versus 98.74 percent. The study [30] proposed a unique hybrid network, the multiple feature-branch convolutional bidirectional recurrent neural network (MFB-CBRNN), to identify MI from 12-lead ECGs. They also developed an optimization strategy called lead random mask (LRM) to reduce the likelihood of overfitting and improve MI detection accuracy. The MFB-CBRNN achieved high accuracy rates in class and subject-based experiments using the PTB dataset. The study [31] presented an automatic and precise approach based on sparse autoencoder (SAE) and TreeBagger to identify and localize MI from single-lead ECG data. The method achieved higher accuracy, sensitivity, and specificity than existing algorithms for MI detection using the PTB dataset. The study [32] developed two methods for MI identification and localization using 12-lead ECG, discrete wavelet transforms (DWT), and end-to-end deep machine learning algorithms. The proposed models were tested on the PTB dataset, achieving high accuracy rates. The study [33] proposed a multi-channel, multi-scale, two-phase deep learning-based approach for detecting MI using VCG signals. The proposed method achieved high accuracy, specificity, and sensitivity using the PTB dataset. The study [34] presented a CNN-based method for automatic MI detection using a novel loss function called focused loss. The proposed method achieved high accuracy, precision, F1 score, and recall using the PTB dataset.

Reference [35] proposed a method for the timely and accurate diagnosis of Inferior MI. They used stationary wavelet transform to decompose the segmented multi-lead ECG signal into sub-bands, and features such as estimated sample entropy, normalized sub-band energy, log energy entropy, and median slope were extracted. The features were then used in combination with gain ratio-based parameter selection to differentiate between healthy participants and Inferior MI patients using support vector machine (SVM) and K nearest neighbor (KNN) algorithms. ECG data from leads II, III, and aVF of participants with IMI and healthy subjects were obtained from the PTB dataset. The proposed method was evaluated from both a theoretical (class-oriented) and practical (subject-oriented) perspective. The class-oriented approach achieved a sensitivity of 98.67%, specificity of 98.72%, positive predictivity of 98.79%, and accuracy of 98.69% using KNN, and a sensitivity of 99.35%, specificity of 98.29%, positive predictivity of 98.41%, and accuracy of 98.84% using SVM, with a ROC of 0.9945% and 0.9994%, respectively. On average, the subject-oriented strategy achieved an accuracy of 81.71%, sensitivity of 79.01%, specificity of 79.26%, and positive predictivity of 80.25%.

The study presented in [36] proposes a CNN architecture to distinguish Inferior MI from healthy signals using raw ECG signal data from leads II, III, and AVF. Using a subject-oriented approach, the model was tested on one patient and trained on the remainder of the PTB database's Inferior MI and healthy signals. The model has 84.54% accuracy, 85.33% sensitivity, and 84.09% specificity. The study [37] developed domain-inspired neural network models to detect myocardial infarction. Initially, they conducted a systematic analysis to determine the contribution of different ECG leads and discovered that data from the v6, vz, and ii leads were crucial for correctly identifying myocardial infarction, which had not been previously reported in the literature. They used this discovery to adapt the ConvNetQuake neural network model for earthquake detection to classify myocardial infarction. Their model had 99.43% record-wise and 97.83% patient-wise classification accuracy.

In addition, the study [38] proposed a ResNet++ model to detect a variety of cardiovascular diseases, including infarction and arrhythmias, using limited ECG leads. The model was trained on the PTB dataset, which includes data from both healthy and unhealthy individuals, and achieved F1-scores of 87% and 89% for identifying Inferior and Anterior wall MI, respectively, outperforming ResNet, which achieved F1-scores of 84% and 87% for Inferior and Anterior wall MI, respectively. The study [39] designed a multi-lead residual neural network (ML-ResNet) model with three residual blocks and feature fusion to detect MI using 12-lead

TABLE 1. Comparison of studies on anterior and inferior MI.

References	Dataset Used	ML Model Employed	Limitations
[36]	PTB Database	CNN	Single-patient testing, limited leads, lack of real-world validation
[37]	PTB Database	Domain-inspired NN	Limited evaluation with other MI types, computational complexities for real-world applications, potential overfitting due to adaptation from unrelated domain
[38]	PTB Database	ResNet++	Limited ECG leads, F1-score disparities, computational complexities for real-world applications
[39]	PTB Database	ML-ResNet	computational complexity for real-time applications

ECG signals from the PTB database. Inter- and intra-patient accuracy rates for the model are 95.49 and 99.92%, respectively. The study [40] proposed an automated approach to detect Posterior MI (PMI) using a 3-lead vector cardiogram (VCG). This method leverages the spatially variable electrical conduction features of cardiac tissue. To address the class imbalance, they introduced a cost-sensitive weighted support vector machine (WSVM) classifier. The proposed method was validated using the publicly available PTB diagnostic dataset, achieving high accuracy, sensitivity, and geometric mean.

Cardiac diagnosis using ECG data with machine learning or deep learning approaches has achieved excellent accuracy. Table 1 presents the comparison of the different studies about Inferior and Anterior MI.

All studies used the PTB dataset, comprising ECG signals of the MI patients. For ECG successful electrode placement on the patient's skin can be uncomfortable, hazardous, and logistically challenging in remote or rural settings. Additionally, electrodes may lose adhesion and degrade the signal, necessitating replacement. To address these challenges, a non-contact approach utilizing UWB signal with deep learning has been proposed to diagnose Inferior and Anterior wall MI. This technique eliminates the need for electrode placement and can be used for remote monitoring or in resource-limited settings. The use of UWB signals with deep learning has the potential to overcome ECG data and electrode placement challenges, making it a promising approach for diagnosing cardiac conditions in challenging settings.

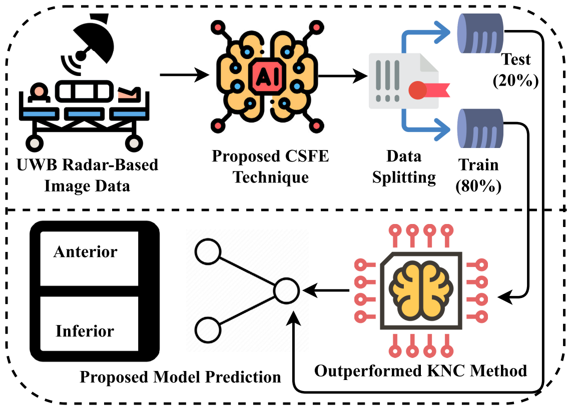

FIGURE 1. Proposed methodology diagram.

(a) (b)

FIGURE 2. (a) Stand designed to mount radar (b) PulseON time domain 410 UWB radar.

III. MATERIALS AND METHODS

A. PROPOSED METHODOLOGY

Figure 1 shows the methodology diagram of the proposed system, which consists of three main stages. The first stage involves data collection. The second stage involves using the convolutional neural network to extract spatial features, which were then used to construct a new feature set through transfer learning. In the third stage, the feature set was split into two portions, with 80% used for training various machine learning (ML) models, and the remaining 20% used for performance evaluation.

1) UWB RADAR-BASED IMAGE DATA

The data was collected from real patients at Sheikh Zayed Medical College and Hospital (SZMC&H), Rahim yar khan, Pakistan, under the supervision of a resident cardiologist. The Khwaja Fareed University of Engineering and Information Technology (KFUEIT) ethics committee provided ethical approval based on the Helsinki Declaration criteria, and a consent form was signed by each subject. At SZMC&H, patient data were collected using PulseON time domain 410 (P410) UWB radar as shown in Figure 2. In a monostatic configuration, separate transmit and receive antennas are used and positioned near together. The FCC-compliant transceiver transmits radio waves in the frequency range of 3.1 GHz to 5.3 GHz (with a central frequency of 4.3 GHz) and a bandwidth of 2.2 GHz.

Patients were asked to lie comfortably on a bed while a radar, mounted on a frame at an average height of 50 cm above the patient's chest, was placed over them, as shown in Figure 3. The radar system emits electromagnetic waves, which encounter interactions with the tissues and structures present in the chest. This interaction results in the generation of a signal response, which is subsequently recorded over a specific period of time. The radar signal data obtained is subsequently recorded in a file format known as comma-separated values (CSV), wherein each row signifies a distinct instance of time during the process of scanning, and each column corresponds to a distinct distance from the radar sensor. The radar received signal is shown in Figure 4 (a). The dataset used in this investigation is collected from 858 patients, with ages ranging between 40 to 70 years, all diagnosed with either Anterior or Inferior wall MI. The dataset includes data from two classes: Anterior MI (435) and Inferior MI (423).

The transmission waveform of a UWB radar is given by [21]:

$$x_t(t, nT) = p(t, nT).sin(\omega_c t) \tag{1}$$

where the pulse generator, denoted as p(t, nT), with "t" representing the time variable in the fast time domain, and "T" representing the pulse repetition period in the slow time domain. The pulse that is bounced back by the subject and detected by the system is presented in Equation (2).

$$x_r(t, nT) = p(t - t_D, nT).sin(\omega_c t - \omega_c t_D) \tag{2}$$

where 'c' is the speed of light and 't_D' is the time delay caused by the transmission path. The pulse of UWB is given by Equation (3) [41].

$$p(t) = \begin{cases} S(t) & a < t < b, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

where S(t) is the UWB radar pulse waveform and a, b is the duration of the pulse, then the pulse train is given by:

$$Ptr(t) = \sum_{k=1}^{k} P(t - (k-1)T_{\text{pr}}) \tag{4}$$

where 'k' is the number of pulses transmitted, and Tpr is the pulse repetition interval. The received signals at the antenna are denoted by a vector $R_k = [s1, s2, s3 \ldots, sk]$.

The radar scan for the time of 3 minutes yields a radargram R. A radargram as shown in 4 (b) is a visual representation of the distribution of reflecting objects in a scanning area as measured by a radar system. It is created by transmitting a series of short-duration pulses into the scanning area and recording the reflected signals from each pulse over a period of time. The recorded data is processed to form a matrix of amplitude values, where each column represents the reflected signals from a single transmitted pulse and each row represents the time delay of the reflected pulse. In the obtained radargram matrix, each column of the radargram R, c, denotes the radar return signal vector in the fast time domain corresponding to the kth transmitted pulse. Each row in the radargram R, r, denotes the radar return signal vector in the slow time domain corresponding to the fast time.

FIGURE 3. Subject during data collection.

To remove clutter from the data, a two-pulse canceller is applied as shown in Figure 4 (c), and the resulting clean data is stored in matrix A. This matrix is then converted to a grayscale image I, which represents the radargram in a visual form. The resulting image can be used to identify and locate reflecting objects within the scanning area, providing valuable information for a variety of applications, including geological surveys, building inspections, and search and rescue operations.

2) PROPOSED CONVOLUTIONAL SPATIAL FEATURE ENGINEERING (CSFE))

The proposed Convolutional Spatial Feature Engineering (CSFE) technique aims to extract features from spatial data, using 2D convolutional layers in CNN architectures. These features provide a rich representation of the data, capturing the spatial characteristics, and can be used for various tasks. The spatial features extracted by 2D convolutional layers can identify subtle patterns and movements. In this manuscript, CSFE features are extracted from greyscale images, and a new feature set is formed along with the labels as shown in Figure 5. This new feature set with the corresponding labels is used to train and evaluate machine learning models to accurately diagnose Anterior and Inferior wall MI. By leveraging the spatial information extracted using the CSFE technique, these models can potentially capture subtle patterns and movements that may be missed by traditional CNNs, leading to improved accuracy in diagnosis.

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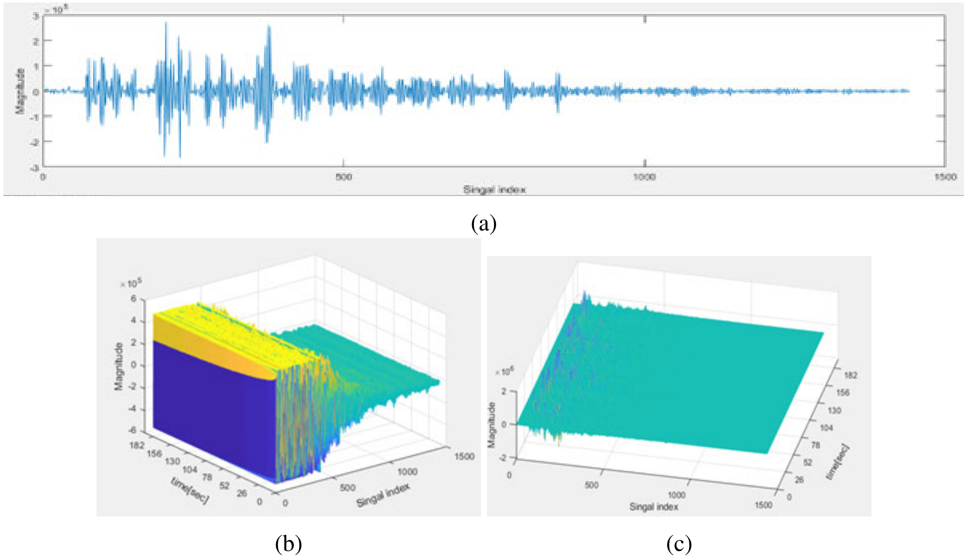

FIGURE 4. (a) Radar Received Signal (b) Set of received UWB raw data matrix R (b) Two-pulse canceller Matrix.

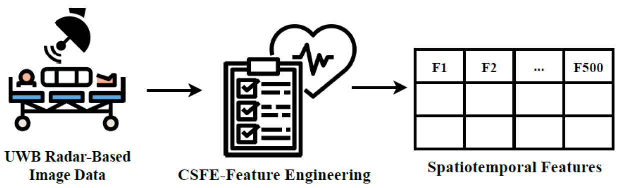

FIGURE 5. The proposed CSFE feature extraction architecture analysis.

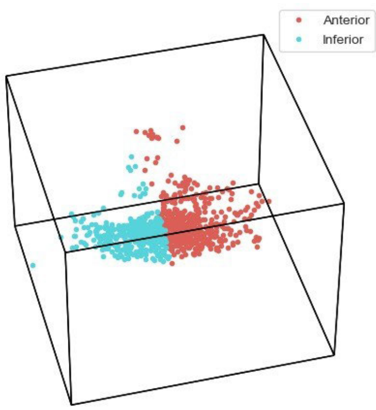

FIGURE 6. Cubic Scatter plot of the features.

From the scatter plot in Figure 6, it is evident that both Anterior and Inferior MI are easily detectable and both have different clusters.

3) SPATIAL FEATURES SPLITTING

In ML, dataset splitting is a critical step that involves dividing available data into training and testing sets. The primary objective of dataset splitting is to create a model that can generalize well to new data, rather than simply memorizing the training data. The standard approach is to divide data into two sets, namely, the training set and the testing set, using a commonly used split ratio of 80:20. In this study, 80% of the data was used for training machine learning models, while 20% was used to evaluate model performance on unseen data. This approach is useful in preventing overfitting and ensuring that the models generalize well to new data. By using a separate testing dataset, the model's accuracy and performance can be assessed on new data, thereby avoiding bias and gaining insights into the model's effectiveness.

B. APPLIED MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

Machine learning and deep learning techniques have demonstrated remarkable success in diagnosing medical conditions [42]. The availability of large quantities of medical data has enabled these techniques to learn from the data and extract valuable insights that enhance the accuracy of disease diagnosis. Convolutional neural networks, a type of deep learning model, have been utilized for image-based diagnosis of diseases, including cancer, Alzheimer's disease, and retinopathy. These models can extract relevant features from medical images, facilitating precise disease classification. Similarly, machine learning algorithms have been employed for diagnosis based on patient medical records and other clinical data. These algorithms can identify patterns in the data that are not apparent to human observers, resulting in accurate diagnoses and tailored treatment recommendations. The application of machine learning and deep learning techniques in medical disease diagnosis has the potential to revolutionize healthcare and improve patient outcomes.

1) CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) have gained significant attention in the medical field for disease diagnosis

TABLE 2. The layered architecture analysis of CNN algorithm.

Layer	Neural Units	Kernal Size	Activation Function
Conv2D	64	(3,3)	activation='relu'
MaxPooling2D	-	(2, 2)	-
Conv2D	128	(3,3)	activation='relu'
MaxPooling2D	-	(2, 2)	-
Conv2D	256	(3,3)	activation='relu'
MaxPooling2D	-	(2, 2)	-
Conv2D	512	(3,3)	activation='relu'
MaxPooling2D	-	(2, 2)	-
Flatten layer	-	-	-
Dense layer	500	-	activation = 'softmax'

due to their ability to analyze and classify medical images effectively. CNNs are a type of deep learning model designed to identify patterns in images through convolutional layers, which help extract features from the input image [43]. In medical diagnosis, CNNs have been used to analyze various medical images such as X-rays, CT scans, and MRI scans to identify and classify diseases. With the aid of these models, doctors and medical professionals can obtain a more accurate diagnosis, ultimately leading to better treatment decisions and patient outcomes. Additionally, CNNs can be used to develop computer-aided diagnosis systems that can provide automated diagnoses based on medical images [44], which can be helpful in resource-limited settings or situations where expert medical opinion is not immediately available. Despite some limitations, CNNs have shown great potential in medical diagnosis and are expected to play a significant role in the future of medical imaging analysis. In addition, the layered architecture analysis of the CNN algorithm is analyzed in Table 2.

2) RANDOM FOREST CLASSIFIER

Random Forest Classifier (RFC) is a popular machine learning algorithm successfully applied to various domains, including medical disease diagnosis [45]. The working of RFC involves the creation of an ensemble of decision trees that make predictions based on the input features. In medical disease diagnosis, the input features can be clinical or biological markers associated with the disease of interest. The RFC works by randomly selecting a subset of features and a subset of data samples to build each decision tree in the ensemble. During prediction, each decision tree in the ensemble makes a prediction, and the final prediction is obtained by taking the majority vote of all the decision trees. This approach helps reduce the model's overfitting and improve its generalization ability. Furthermore, the RFC also provides an estimate of the importance of each input feature, which can be used to identify the most relevant markers for disease diagnosis. Overall, the RFC is a powerful tool for medical disease diagnosis that can improve the accuracy and efficiency of the diagnostic process.

3) DECISION TREE CLASSIFIER

Decision Tree Classifier (DTC) is a popular algorithm used in machine learning for solving classification problems. In medical disease diagnosis, DTC can predict the presence or absence of a particular disease based on a set of symptoms or risk factors [46]. The DTC creates a tree-like model where each internal node represents a test on a specific feature, and each leaf node represents a class label. The DTC algorithm iteratively partitions the feature space based on the most informative features, such as the presence or absence of a particular symptom or risk factor. The partitioning process continues until the algorithm reaches a stopping criterion, such as a minimum number of samples per leaf or a maximum tree depth. The resulting decision tree can classify new, unseen data by traversing the tree from the root node to a leaf node corresponding to the predicted class label. In medical disease diagnosis, DTC can provide a transparent and interpretable way to make predictions and assist healthcare professionals in making accurate diagnoses.

4) SUPPORT VECTOR MACHINE

Support Vector Machines (SVM) is a popular machine learning technique applied to various areas, including medical diagnosis [47]. SVM is a supervised learning algorithm that can be used for binary or multi-class classification problems. In medical diagnosis, SVM is used to classify patient data into healthy or diseased categories based on various clinical parameters. SVM works by finding the best hyperplane that separates the data into two classes with the maximum margin. The hyperplane is chosen to maximize the distance between the closest points of both categories, which results in better generalization performance of the model. In medical diagnosis, SVM can be used with different kernels, such as linear, polynomial, or radial basis functions, to achieve better classification accuracy. SVM has been successfully applied to several medical diagnoses problems, such as diabetes, breast cancer, and heart disease, with promising results. SVM provides a robust, efficient, and accurate classification model for medical diagnosis, which can help improve disease diagnosis and treatment decisions.

5) SGD CLASSIFIER

A stochastic Gradient Descent Classifier (SGDC) is a popular machine learning algorithm used for medical dis-ease diagnosis [48]. The SGDC algorithm is a linear classifier that uses the stochastic gradient descent optimization method to minimize the cost function. It is commonly used for binary classification tasks and is known for its efficiency and speed in handling large datasets. In medical disease diagnosis, SGDC can be used to classify patients as either having a disease or not based on various medical features such as symptoms, medical history, and test results. The algorithm learns from historical patient data to identify patterns and make accurate predictions about the disease status of new patients. The effectiveness of SGDC for medical disease diagnosis depends on the quality of the training data, the selection of relevant features, and the choice of hyperparameters such as learning rate and regularization. Despite some limitations, SGDC has shown promising results in various studies and can

TABLE 3. The hyperparameters optimization analysis.

Model	Hyperparameters
RFC	max_depth=300, random_state=0, n_estimators=300
DTC	max_depth=300, random_state=0
SVM	gamma='auto', kernel='linear'
SGDC	max_iter=1000, tol=1e-3
KNC	n_neighbors=2
CNN	optimizer='adam', loss='binarycrossentropy'

be helpful for healthcare professionals in aiding diagnosis and treatment decisions.

6) K-NEIGHBORS CLASSIFIER

K-Neighbors Classifier (KNC) is a popular machine learning algorithm that is often used for medical disease diagnosis [49]. The KNC algorithm works by classifying new data points based on their proximity to existing data points in a training dataset. In the context of medical disease diagnosis, the KNC algorithm uses features such as symptoms, patient history, and medical test results to identify patterns indicative of a particular disease. One of the key advantages of the KNC algorithm for medical disease diagnosis is that it is a non-parametric method. Overall, the KNC algorithm is a valuable tool for medical disease diagnosis, as it can help clinicians identify patterns in patient data that may indicate particular diseases.

7) HYPERPARAMETER TUNING

Hyperparameter tuning is a crucial step in developing machine learning models, where a set of parameters is selected to optimize the model's performance hyperparameter. These parameters, known as hyperparameters, are not learned during training. The process of hyperparameter tuning involves systematically exploring different combinations of hyperparameters to find the optimal set of values that leads to the best performance of the model. This is often an iterative process that can be time-consuming, requiring a deep understanding of the model architecture and the problem domain. Hyperparameter tuning can significantly improve the accuracy of machine learning models and is essential for achieving state-of-the-art results in many real-world applications. The hyperparameters optimization analysis is described in Table 3.

IV. RESULTS

Machine learning has shown great potential in improving medical diagnosis accuracy and efficiency in recent years. Much research has been conducted to explore the use of machine learning models for diagnosing various diseases. The results validations, and discussions of our proposed study are analyzed in this section. Results of the applied model in comparisons and their evaluation metrics are also discussed.

This study's experimental setup involved utilizing the Google Colab environment with a graphical processing unit (GPU) backend, which provides efficient processing capabilities. The system used in the experiment had 13 GB RAM and 90 GB disk space, providing sufficient memory and storage for the tasks at hand. The Python 3 programming language was used to build machine and deep learning models due to its flexibility and ease of use. The models were evaluated by measuring parameters such as runtime computation, accuracy, precision, recall, and F1 score, which are critical in determining the performance and effectiveness of the models developed. The dataset includes observations from two classes: Anterior MI infarction (435) and Inferior MI infarction (423) as shown in Figure 7.

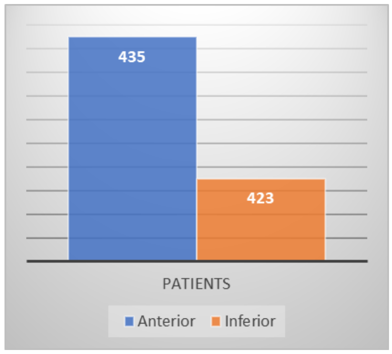

FIGURE 7. Distribution of Labels.

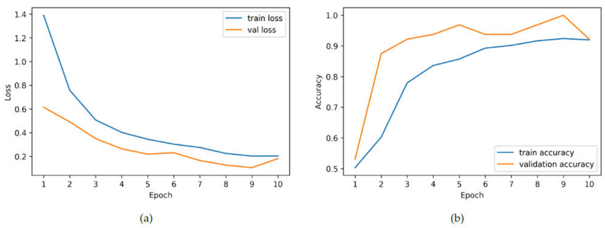

FIGURE 8. The time series-based performance analysis of conventional neural network during training.

A. RESULTS WITH CONVENTIONAL NEURAL NETWORK

The performance results with the classical conventional neural network are analyzed in this section. The time series-based performance validation of the applied conventional neural network during training is analyzed in Figure 8. The analysis shows that the training loss score values are high during the first three training epochs. Low accuracy scores are achieved during the first three epochs of training. With the increase in the number of epochs, the loss scores are decreased, and the accuracy scores are increased. The analysis concludes that the applied conventional neural network achieved above 80% accuracy at the final epoch.

The comparative performance results of applied classical conventional neural networks for unseen testing data are analyzed in Figure 9. The bar chart analysis is based on accuracy, precision, and f1 metrics scores. The model achieved an accuracy score of 87%, a precision score of 76%, and an f1 score of 86%. Only the precision metric scores are less in comparison.

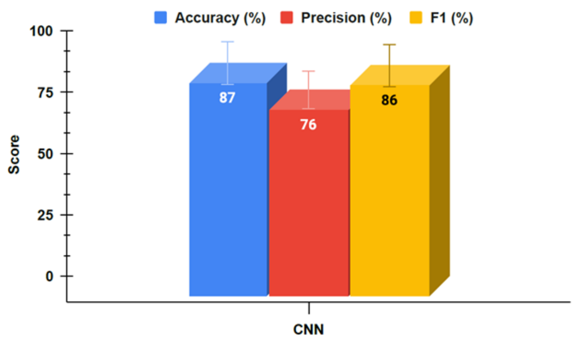

FIGURE 9. The performance metrics analysis of conventional neural network for unseen test data.

TABLE 4. Results comparisons with the proposed CSFE-based feature extraction technique.

Model	Accuracy	Precision	Recall	F1-score
RFC	0.84	0.84	0.84	0.84
DTC	0.70	0.70	0.70	0.70
SVM	0.49	0.24	0.49	0.33
SGDC	0.51	0.26	0.51	0.34
KNC	0.98	0.98	0.98	0.98

The analysis concludes that the applied classical conventional neural network achieved acceptable scores, however not the highest, which can be further improved.

B. RESULTS WITH TRANSFER FEATURES

The comparative performance results with the transfer learning-based features are analyzed in Table 4. The comparative performance analysis is based on accuracy, precision, recall, f1-score, and class-wise report.

The analysis shows that the applied DTC, SVM, and SGDC models achieved poor performance scores. The applied RFC method achieved an acceptable performance score in comparison, but not the highest. Finally, the proposed KNC model achieved the highest performance accuracy score of 98% for detecting the Anterior and Inferior patients using the transfer features. The bar chart-based performance comparison analysis of applied machine learning models with the proposed CSFE feature extraction technique is illustrated in Figure 10. The analysis shows that SVM and SGDC achieved very poor performance scores with transfer features. The applied RFC and DTC techniques achieved an acceptable score but not the highest. The proposed KNC method achieved the highest scores for all performance metrics in comparison.

The performance scores of each applied machine learning method are summarized using the confusion matrix analysis, as shown in Figure 11. The confusion matrix is based on the difference between the actual and predicted classes, which shows the error rate applied models achieve. The analysis shows that the RFC, DTC, SVM, and SGDC achieved a high error rate in comparison. The analysis concludes that the proposed KNC technique achieved less error rate, validating the high-performance scores.

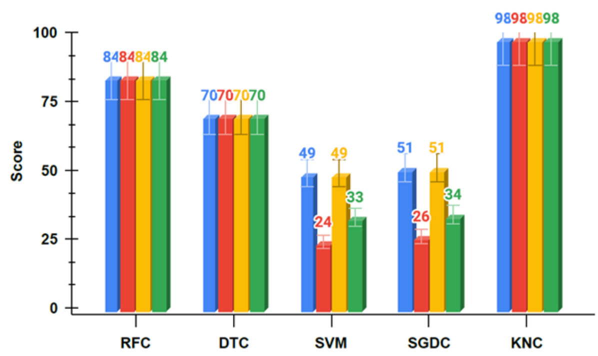

FIGURE 10. The bar chart-based performance comparison analysis of applied technique with proposed.

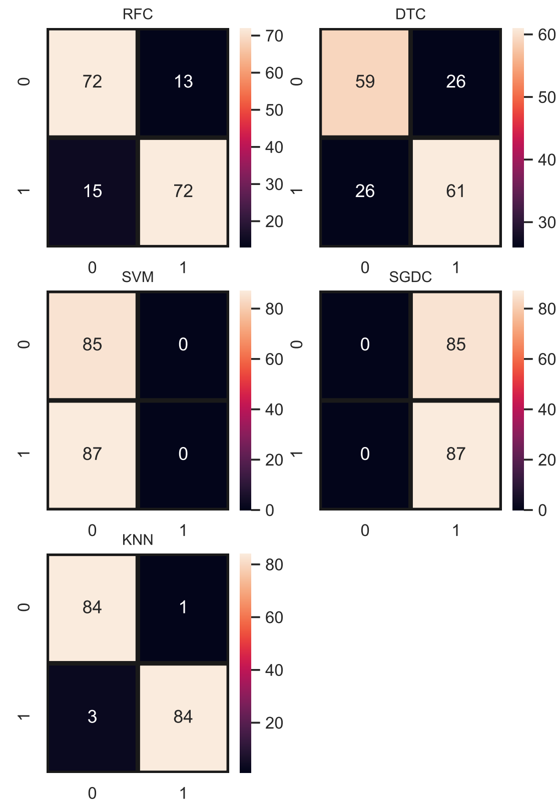

FIGURE 11. The confusion matrix analysis of applied machine learning techniques.

C. K-FOLD CROSS-VALIDATION ANALYSIS

The k-fold cross-validation analysis is applied to validate the performance of each machine-learning technique as described in Table 5. The transfer features dataset is divided into 10 folds to validate the generalization of applied techniques. The cross-validation analysis shows that the DTC, SVM, and SGDC techniques achieved low k-fold performance scores with high standard deviation values. The proposed KNC achieved the highest k-fold accuracy score of 98% with low standard deviation values. The analysis

TABLE 5. The K-fold cross-validation performance analysis of applied techniques.

Technique	Accuracy (%)	Standard Deviations (+/-)
RFC	0.84	0.0301
DTC	0.67	0.0442
SVM	0.46	0.0541
SGDC	0.48	0.0484
KNC	0.98	0.0101

TABLE 6. The runtime computations complexity analysis of applied techniques.

Technique	Runtime computations (Seconds)
RFC	2.365
DTC	0.231
SVM	0.142
SGDC	0.018
KNC	0.044

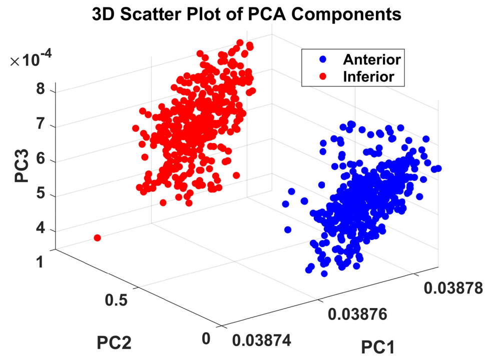

FIGURE 12. The feature space representation analysis of extracted transfer learning-based spatial features.

concludes that all applied techniques are generalized for predicting the Anterior and Inferior patients using the transfer features.

D. COMPUTATION COMPLEXITY ANALYSIS

The runtime computation complexity analysis of applied machine learning with transfer features is analyzed in Table 6. The analysis shows that the RFC technique achieved the highest computation score values. The proposed KNC technique achieves the minimum runtime computation complexity score of 0.018 seconds. The analysis concludes that our proposed study approach is computationally less complex and efficient in detecting Anterior and Inferior patients.

The findings derived from the machine learning models displayed in Table 4 and 5 offer significant insight that can be applied in clinical settings. In the context of clinical environments, achieving a high level of precision is frequently considered crucial, particularly in situations where the occurrence of false positives is a cause for concern, as shown in disease diagnostics, such as cancer detection. Ensuring a high recall rate is of utmost importance in situations when the consequences of failing to identify positive cases are significant, such as in the detection of infectious diseases. Achieving a favorable equilibrium between precision and recall, as shown by a high F1-score, is considered optimal for generating dependable predictions. The computational performance and results of each model indicate that KNC exhibits efficiency, rendering it advantageous for the purpose of real-time clinical decision-making.

E. TRANSFER FEATURE SPACE VALIDATAION

The feature space validation analysis of extracted transfer learning-based spatial features is illustrated in Figure 6. The direct visualization of a dataset with a high number of dimensions poses significant challenges, primarily stemming from the inherent constraints of human perception. Nevertheless, it is possible to employ dimensionality reduction techniques and other visualization methods in order to investigate and acquire valuable insights from datasets with a high number of dimensions. A frequently employed strategy involves the utilization of dimensionality reduction methodologies such as Principal Component Analysis (PCA) or t-SNE to map the data onto a reduced-dimensional space, either two-dimensional or three-dimensional while maintaining specific structural characteristics intact. Principal Component Analysis (PCA) is applied to the dataset, resulting in the generation of a three-dimensional scatter plot. The first three principal components are utilized as the respective x, y, and z axes for the plot. The feature space representation is based on extracted feature values corresponding to the target class Anterior and Inferior. The analysis demonstrates that transfer learning-based spatial features are more linearly separable compared to the UWB radar-based image data for applied machine learning techniques. This more linearly separable behavior of data results in achieving high-performance accuracy scores in this study.

V. CHALLENGES AND LIMITATIONS

Although the presented study demonstrates significant advancements in the field of myocardial infarction (MI) detection and classification, it is crucial to recognize certain challenges and limitations that necessitate careful attention.

- The present study makes use of a recently developed dataset that relies on Ultra-Wideband (UWB) radar signals. Nevertheless, it is important to consider that the size and variability of this dataset could potentially impact the extent to which the findings can be applied to a broader population. The model's capacity to effectively address the complexities and subtleties inherent in real-world situations can be augmented by the inclusion of a more comprehensive and heterogeneous dataset.
- Although the Convolutional Spatial Feature Engineering (CSFE) technique we have suggested demonstrates promising outcomes, doing a thorough comparative analysis with other feature extraction methods or current techniques from the literature would enhance our comprehension of its strengths and weaknesses.
- The dataset and models employed in our investigation may exhibit specificity towards a certain

community or demographic. Caution and validation are necessary when extrapolating the findings to diverse populations characterized by varying genetic backgrounds, lifestyles, and healthcare systems.

VI. CONCLUSION

Cardiovascular disease is recognized as a prominent worldwide contributor to mortality. The monitoring of electrocardiograms (ECGs) and the timely detection of abnormalities have a crucial role in reducing death rates associated with myocardial infarction. Therefore, the development of a non-invasive approach that can effectively and accurately categorize various forms of myocardial infarction would be highly advantageous. This study proposes the use of advanced deep and machine learning techniques for the detection and classification of patients with Anterior and Inferior myocardial infarction. To conduct the experiments, a newly created dataset consisting of Ultra-Wideband radar signal-based images was used. A novel technique, called convolutional neural network-based spatial features (CSFE) was proposed to extract spatial features from the dataset. The study compares the performance of several machine learning techniques, including random forest, decision tree, support vector machine, stochastic gradient descent classifier, and k-nearest neighbors with the applied deep learning technique, convolutional neural network. The results of the study indicate that the advanced machine learning techniques, when used with the proposed CSFE technique, achieved high-performance accuracy scores. Specifically, the k-nearest neighbors' technique outperformed the other techniques, achieving a high-performance accuracy score of 98% for detecting Anterior and Inferior patients. The methods used in the study were fully hyperparameter tuned, and the performance was validated using the k-fold cross-validation method. For future work, the study aims to apply advanced pre-trained neural network techniques to enhance performance and collect more Anterior and Inferior related patient datasets.

COMPETING INTERESTS

The authors declare that they have no competing interests.

AUTHORS CONTRIBUTIONS

- Kainat Zafar: Conceptualization, data curation, formal analysis, writing—original draft, methodology, investigation.
- Hafeez Ur Rehman Siddiqui: Methodology, investigation, software, supervision.
- Abdul Majid: Investigation, data curation.
- Adil Ali Saleem: Visualization, validation, software, investigation
- Ali Raza: Writing—original draft, validation, software.
- Furqan Rustam: Writing—review and editing, validation, investigation.
- Sandra Dudley: Resources, supervision.

ETHICAL AND INFORMED CONSENT FOR DATA

"Ethical considerations and informed consent were obtained for data collection in this study. The research protocol and procedures were reviewed and approved by the Khawaj Fareed University and Sheikh Zayed Medical College and Hospital, Rahim Yar Khan, Punjab, Pakistan. Participants involved in the study were provided with a consent form that outlined the purpose of the research, the nature of their involvement, and the measures taken to ensure confidentiality and data protection. The dataset didn't contain any personal information about the Participants."

DATA AVAILABILITY

The data used in this study is available upon request. Interested researchers can contact Dr. Hafeez Ur Rehman Siddiqui (hafeez@kfueit.edu.pk) to request access to the data. Requests will be reviewed and evaluated in accordance with the ethical and legal guidelines governing data sharing.

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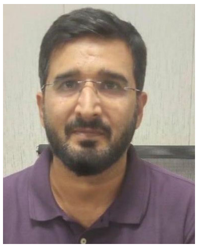

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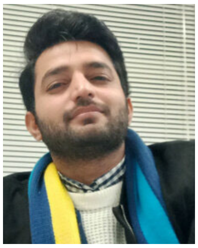

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