

# Automated Diagnosis of Mitral Valve Diseases Using Echocardiographic Images: A Comparative Study of GLCM Features and Deep Learning Techniques

Hani Attar<sup>1,2,\*</sup>, Jafar Ababneh<sup>3</sup>, Omar A. Sarhan<sup>4</sup>, Ahmed Hamdy<sup>4</sup>, Mohamed Hafez<sup>5,6</sup>, and Mohanad A. Deif<sup>4,7,\*</sup>

<sup>1</sup>Faculty of Engineering, Zarqa University, Zarqa, Jordan College of Engineering, Zarqa, Jordan

<sup>2</sup>College of Engineering, University of Business and Technology, Jeddah, Saudi Arabia

<sup>3</sup>Cyber Security Department, Faculty of Information Technology, Zarqa University, Zarqa, Jordan

<sup>4</sup>Department of Computer Science, College of Information Technology, Misr University for Science and Technology (MUST), Giza, Egypt

<sup>5</sup>Faculty of Engineering FEQS, INTI International University, Nilai, Malaysia

<sup>6</sup>Faculty of Management, Shinawatra University, Pathum Thani, Thailand

<sup>7</sup>Research Institute of Sciences and Engineering, University of Sharjah, United Arab Emirates

Email: hattar@zu.edu.jo (H.A.); jababneh@zu.edu.jo (J.A.); Oma.sarhan@must.edu.eg (O.A.S.); A.hamdy@must.edu.eg (A.H.); mohdahmed.hafez@newinti.edu.my (M.H.); mabdelhamid@sharjah.ac.ae (M.A.D.)

\*Corresponding author

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**Abstract**—Mitral Valve (MV) pathologies such as Mitral Valve Prolapses (MVP), Mitral Stenosis (MS), and type III regurgitation should be diagnosed as early as possible for the better management of the patients. This research work presents a method for the classification of MV diseases using echocardiographic images and texture analysis of the images using Gray Level Co-occurrence Matrix (GLCM) features in conjunction with Machine Learning (ML) classifiers. Initially, a Convolutional Neural Network (CNN) was employed to categorize echocardiographic images into two standard views: Apical Four-Chamber (A4C) and Parasternal Long-Axis (PLA). Next, the energy, contrast, correlation, and the entropy of GLCM-based texture features were obtained. The features were then fed into ML classifiers such as Random Forest (RF), Neural Networks (NN), Ensemble models to classify MV conditions. In the A4C view, the Neural Network Classifier (NNC) obtained an accuracy of 85% while in the Parasternal Long Axis (PLA) view, the accuracy was 84%. Some of the features of GLCM that were deemed important in the performance of the model were revealed. The results show that combining GLCM texture analysis with ML provides a potential way of improving the precision and reliability of MV disease diagnosis. The findings of this study contribute to advancements in cardiovascular disease detection by integrating machine learning techniques with echocardiographic analysis, ultimately supporting efforts to enhance public health and early disease diagnosis, in alignment with global healthcare initiatives.

**Keywords**—Gray Level Co-occurrence Matrix (GLCM), echocardiography, medical imaging, machine learning, mitral valve diseases

## I. INTRODUCTION

### A. Clinical Background

Mitral Valve (MV) diseases are serious causes of cardiac morbidity and mortality worldwide, and these include Mitral Valve Prolapse (MVP) and Mitral Stenosis (MS). In the earlier work by Omar Ahmed *et al.* [1], Deep Learning (DL) models, specifically ResNet50, were able to classify different views of echocardiograms with an accuracy of 98.65% for both Parasternal Long Axis (PLA) and Apical Four-Chamber (A4C) views. The following paper is an advancement towards the previous study by the authors in the arena of automatic classification of MV diseases using machine learning

classifiers with the Gray Level Co-occurrence Matrix GLCM features for improved diagnostic capabilities [2, 3].

In the absence of proper management and treatment, MVP and MS may culminate in serious implications, including heart failure, atrial fibrillation, and sudden cardiac death. MVP is typified by the failure of the valve leaflets to close properly, frequently resulting in mitral regurgitation, leaving blood to leak backward into the left atrium. On the other hand, in MS, the MV opening is narrowed, limiting the flow of blood from the left atrium into the left ventricle, which directly increases the pressure within the atrium that may lead to pulmonary congestion and right heart. Fig. 1 shows examples of echocardiographic views.

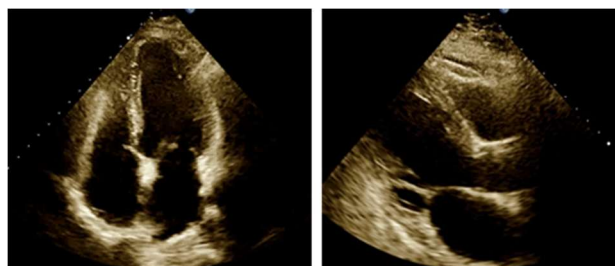


Fig. 1. Examples of echocardiographic views.

Global prevalence of MV diseases varies throughout the world, apparently by the factors of age, sex, and geographic locale. For example, MVP is more prevalent in females and can be detected in 2–3% of the general population. MS often is sequelae of rheumatic fever, but remains endemic in developing countries, where rheumatic heart disease is more frequent. The impact of MV diseases on available public health systems is greatly significant, and it is vital to have effective diagnostic and therapeutic mechanisms in place. Proper and timely diagnosis of MV diseases is an imperative aspect of best patient care. Early disease detection allows an appropriate choice and timing of medical or surgical therapy, improving quality of life and patient outcome respectively. However, the diagnosis of MV diseases across a wide spectrum is challenging, demanding detailed imaging and expert interpretation to differentiate between various

conditions and their severities.

### B. Importance of Echocardiography in Diagnosis

Echocardiography has become the mainstream for all cardiac imaging applied to diagnosis and disease management in the progression of heart diseases, and that, of course, includes MV diseases, which is non-invasive technique uses ultrasound waves to produce detailed images of the structures of the heart and assess its function in real-time. The high-resolution images provided by echocardiography make it possible for the clinicians to have an accurate assessment of the anatomy and hemodynamics of the MV.

There are a lot of echocardiographic views that are in use for the assessment of MV diseases, and among these, the PLA and A4C are the most informative as shown in Fig. 1. The PLA view, for instance, offers a sagittal plane of the heart, and hence the echocardiographer can appreciate the left atrium, left ventricle, aortic root, and the relation of the MV with the neighboring structures, which is primarily useful for the assessment of the mitral annulus-aortic junction distance, which is used as a reference concerning the valve's morphology and the degree of prolapse or stenosis. The A4C view, on the other hand, offers a coronal plane view and is further helpful in producing a comprehensive assessment of the left and right atria and ventricles. The global function can be evaluated, and more importantly, any regurgitation or stenosis of the MV is demonstrated. The anatomical and functional details gained from such views are, therefore, necessary for the evidence-based diagnosis and management of diseases of the MV. In particular, echocardiography can identify pathological features that include thickened valve leaflets, restricted leaflet motion, and regurgitant jets, suggestive of a variety of MV conditions.

### C. Current Diagnostic Challenges

The improvement in the echocardiographic technology notwithstanding, the integrity of echocardiographic images is still a daunting task, with the major reliance being on the skills and experience of the echocardiographer. Several initial factors contribute to these challenges, including the innate variability of the anatomical presentations, the dynamic nature of the cardiac function, and the subtlety of early pathological changes. A notable limitation is inter-observer variability in image interpretation between different echocardiographers of varying expertise and experience. Experienced clinicians can make an informed diagnosis by providing a classification of MV diseases, which is not universally available, hence the diagnostic accuracy varies. In addition, the time needed for interpretation limits its application in the high-throughput clinical setup and emergent scenarios that call for fast decision-making. Another crucial limitation is the difficulty in detecting subtle or early-stage abnormalities. Finally, several cardiac function factors are dynamic and, therefore, complicate diagnosis. Consequently, some pathological features may be detectable or visible in just one phase of the cardiac cycle. For example, MVP could be maximal in systole, and MS could be more appreciated in diastole. Therefore, an appropriate and accurate diagnosis requires a detailed analysis of the motion of the valve throughout the cardiac cycle, which is time-consuming and human-dependent and is hence subject to

some human errors.

The current diagnostic defects result in the need for automated, accurate, and efficient diagnostic tools that will assist clinicians in the interpretation of echocardiographic images. ML and DL technologies will improve the current state of affairs by providing consistent, reproducible, and rapid interpretations of complex medical images.

### D. Machine Learning and Deep Learning in Echocardiography

The ML and DL are subsets of Artificial Intelligence (AI) that have, in turn, changed various fields, among them medical imaging. ML involves algorithms that can learn patterns from data and make predictions. On the other hand, DL is a subset of ML that uses deep neural networks with multiple layers to model complex patterns of relationships in the data. In the medical imaging arena, ML and DL techniques have been applied to image segmentation, feature extraction, and disease typing. Such technologies scan a large dataset of medical images to identify patterns that may imply the presence of particular diseases, thereby enhancing diagnostic accuracy and reproducibility.

Convolutional Neural Networks (CNNs) being a sub-class of the DL models, have shown remarkable performance in image recognition tasks. CNNs have been applied in echocardiography to classify views automatically, detect pathological conditions, and measure quantitatively the parameters of cardiac functions like ejection fraction. Such automated systems reduce the workload for a physician and at the same time reduce the variations in image acquisition, hence reducing the variations in image interpretation, thereby providing more reproducible and reliable diagnostic results.

### E. Integration of GLCM Features in Echocardiographic Analysis

The Gray-Level Co-occurrence Matrix is a texture analysis statistical technique in the image, which denotes the spatial relationship between pairs of pixels depending on their intensity values, which gives a detailed informative texture knowledge, which can be decisive in differentiating between tissue types or pathological states. Features like energy, contrast, correlation, and entropy from the GLCM are commonly used in medical images in such a way that to make them add power to the diagnostic power of ML models. Therefore, the integration of GLCM features with machine classifiers allows us to combine the detailed texture analysis provided by GLCM with the powerful pull of ML classifiers to enhance the echocardiographic classification process. The robustness of the approach lies in the fusion of the power of feature extraction methods with the capabilities of ML pattern recognition.

### F. Motivation and Objectives

The motivation of this study is to develop more accurate, efficient, and automated diagnostic tools for MV diseases using echocardiographic images as shown in Fig. 2. Since the increase in the prevalence and the significant impact of MV diseases, the demand for a reliable diagnostic method that can support the clinical issue diagnosis and classification in an accurate and timely manner has become very indispensable. This study aims to evaluate the potential of the classification of echocardiographic perspectives based on GLCM feature

extraction for diagnosing MV diseases. The specific objectives are:

The GLCM feature extraction process, illustrated in Fig. 3, involved the following steps:

- Extracting GLCM features from echocardiographic images for both the PLA and A4C views.
- Training Random Forest classifiers to assess their effectiveness in identifying MV diseases.
- Comparing the classification performance of Random

Forest with other ML models, such as Neural Networks and Ensemble models.

These objectives will be achieved through the design of a comprehensive framework for automated analysis of echocardiographic images towards a boost in the diagnostic capacities for MV diseases. The framework will improve not only diagnostic accuracy but also lessen the variability and workload of manual image interpretation.

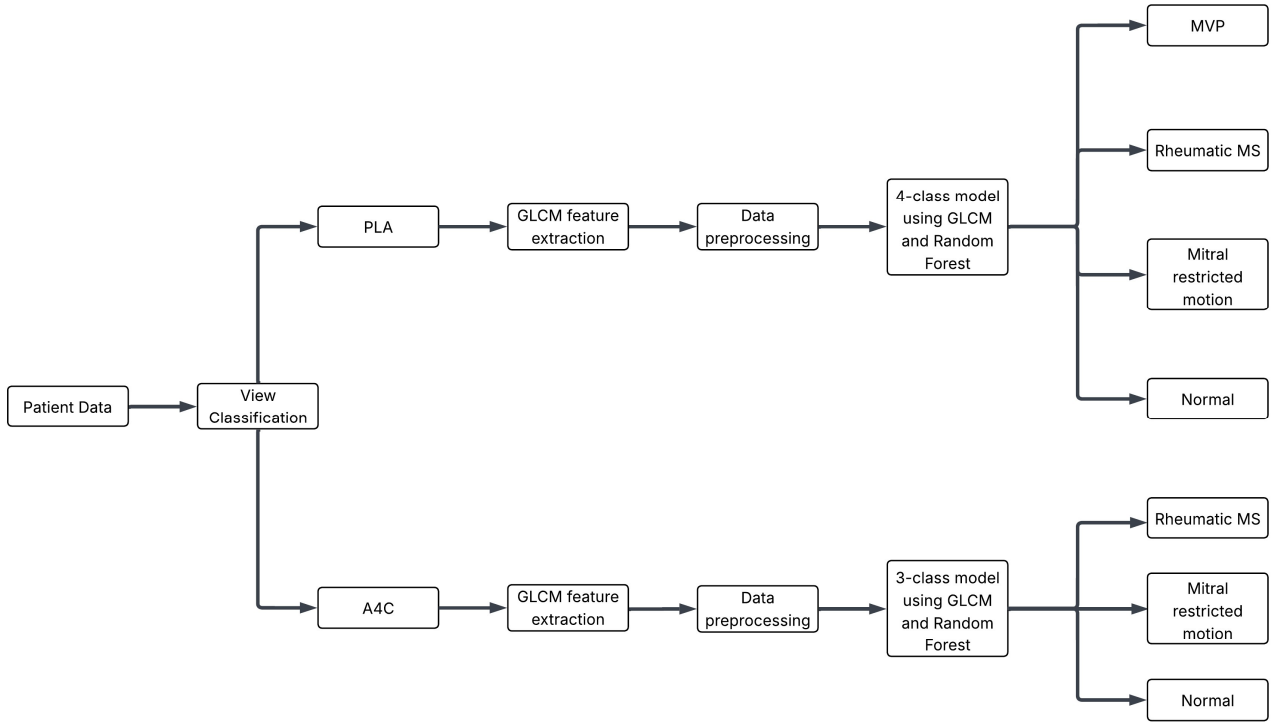


Fig. 2. Workflow of the study.

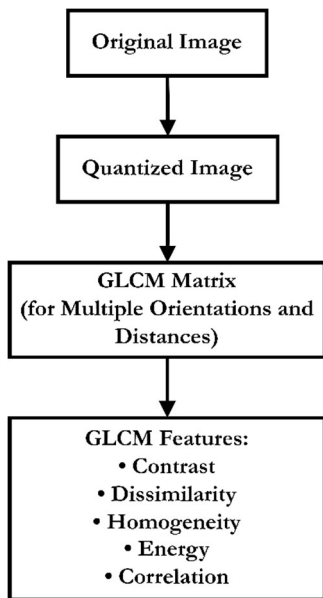


Fig. 3. GLCM feature extraction process.

## II. RELATED WORKS

### A. Deep Learning in Echocardiography

DL has contributed remarkably to the analysis of echocardiography—automated diagnosis with high power

and diagnostic accuracy. Several works have come up showing DL models applied to echocardiographic images. Madani *et al.*, in [2], came up with an innovative deep-learning model for the automated classification of echocardiographic views and the detection of cardiovascular diseases based on echocardiographic images. They could have the system reach a very high level of accuracy in distinguishing different echocardiographic views, which showed that DL had the potential to minimize manual interpretation reliance and enhance diagnostic consistency. In the variability in image presentation and the dynamic nature of the cardiac function, Vafaezadeh *et al.* [3] focused on the morphological classification of MV diseases using DL. the use of Carpentier's functional classification approach and fine-tuned pre-trained CNNs were made use of in the classification of the Normal MV, MV Prolapse, Rheumatic MS, and Restricted Leaflet Motion. The study, which also made use of Grad-CAM for model explainability, achieved an 80% accuracy rate by indicating the potential of DL for fast and keen providing of MV pathologies. developed a DL model for the interpretation of the echocardiogram, specifically for view classification, disease detection, and cardiac function quantification. Their model showed that automated technologies could be effectively integrated into routine clinical practice to decrease clinicians' workload and

enhance the diagnosis's precision and consistency.

### B. Improving Diagnostic Accuracy with Feature Extraction

Feature extraction is a process that allows the performance of medical images to improve; GLCM is one such technique that gives a comprehensive look at the textures. It has been also widely applied in medical imaging to improve the diagnostic capabilities of machine-learning models. Ouyang *et al.* [4], researched using AI technology to automate the diagnosis of heart diseases from echocardiographic images. They emphasized developing models that would be capable of generalizing to patient diversity and different imaging protocols. They further emphasized the strong necessity for clinical validation to ensure model applicability in practice. Chen *et al.* [5] conducted a survey of various deep-learning models in automatic segmentation for the cardiac chamber on echocardiographic images. These models, like the CNN, and the active contour models, improved the accuracy of the ejection fraction measurements and the assessments of myocardial functions. Automated segmentation not only reduced the time required to manually analyze but also increased the reproducibility of measurements, which is a vital factor in patient monitoring and decisions on treatment plans. The hybrid model approach proposed by Zhang *et al.* [6], incorporates concatenating the GLCM features and the CNN framework for the automatic classification of echocardiographic. The classification method integrated the strengths of both methodologies; integrating the strengths of both methodologies decreased the error rate, producing better classification performance than either method could provide solely [7]. It is just the beginning, and there is a lot of potential in integrating traditional feature extraction techniques with modern DL frameworks to get improved diagnostic outcomes of echocardiography.

### C. Real-World Applications and Challenges

The application of ML and DL models to real-world clinical practices is brought down by the general need for large datasets that have been annotated, the need to generalize the models to support imaging variability, and the need to integrate seamlessly into the current clinical workflow. The models developed by Lin *et al.* [8] for the automatic detection of mitral regurgitation in pediatric echocardiograms have shown high diagnostic accuracy, which has been shown in their model and can guide the clinical decision-making processes about the specialized patient group. However, the authors noticed some challenges that underlie the quality of their data and the necessity of clinical validation of their findings. Liu *et al.* [9] developed a DL framework for echocardiography supporting diagnosis with lesion localization and anomaly detection. This work is important for model explainability, which can lead to the kind of trust among clinicians that is key to clinical adoption using such technologies. They use techniques like Grad-CAM visualization to make the model's prediction visually

explainable to the user, hence increasing the interpretability of the model.

### D. Comparative Analysis

The first work to be based on the richness of texture analysis provided by GLCM features but using classical ML classifiers. DL methods have recently made vast progress in automating the process. However, they rely on large data quantities and substantial computational resources. Feature extraction methods, such as GLCM, are highly computationally efficient and can effectively be used with small sample sizes. In comparison with other similar works, such as [2, 3], which mainly are based on DL models, our approach—that of building the classifier using GLCM features—gives a more interpretable and explainable methodology. The chosen features, in this case, features like energy, contrast, and entropy, are features that can be directly linked with specific pathological conditions and hence provide clinicians with important insight into the diagnostic process. Further, combining the GLCM features with ML classifiers, as demonstrated in Ref. [6], leads us to show the hybridization of classical and modern techniques to attain the best possible diagnostic performance. Our study is an extension of the same, and the results for classification accuracy are depicted along with classifiers like Random Forest, neural networks, and ensemble models.

### E. Future of Research in the Area

GLCM feature integration with DL models is an area of extensive exploration. The datasets can be expanded further to include all imaging protocol modes and patients with much more variation in characteristics. For translating these technologies to actual clinical use, the imperative is to develop AI models to improve the interpretation of the research further and to develop real-time analysis.

## III. METHODOLOGY

Fig. 4 illustrates the methodological workflow of our study, providing a structured overview of the key stages from dataset collection to classification and performance evaluation. The process begins with dataset collection, where echocardiographic images are gathered. These images undergo preprocessing, which includes normalization, denoising, and gray-level quantization to ensure data consistency and enhance image quality. Following this, feature extraction is performed using GLCM features, specifically focusing on energy, contrast, correlation, and entropy to capture crucial textural patterns. The extracted features are then fed into three different classification models—Random Forest, Neural Network, and Ensemble methods—each playing a role in identifying mitral valve diseases. Finally, the models' performance is evaluated using accuracy, precision, recall, F1-Score, and confusion matrices, allowing a comprehensive assessment of the effectiveness of each classifier. This structured workflow enhances the reproducibility of the study and ensures a systematic approach to automated echocardiographic analysis.

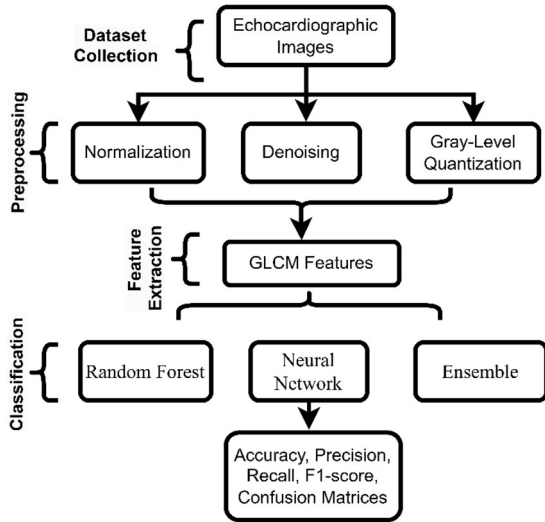


Fig. 4. Workflow of the proposed echocardiographic image classification framework.

#### A. Dataset

The dataset used in this study consists of 1773 echocardiographic cases, including both Apical 4-Chamber (A4C) and Parasternal Long-Axis (PLA) views. The images were collected from echocardiographic studies performed at Tehran Heart Center, Iran, and were manually annotated by expert cardiologists following Carpentier's functional classification. The dataset is categorized into four classes based on mitral valve (MV) abnormalities:

- Normal MV cases: 424
- Type II (Mitral Valve Prolapse—MVP) cases: 155
- Type IIIa (Rheumatic Mitral Stenosis—MS) cases: 392
- Type IIIb (Restricted mitral motion) cases: 802

The echocardiographic images were captured using a Philips Affinity 70C ultrasound system equipped with an S5-1 probe, operating at an average frame rate of  $41 \pm 8$  frames per second. Each echocardiographic movie was converted into a sequence of frames for analysis, with an average image resolution of  $800 \times 600$  pixels. The dataset was split into 80% training, 10% validation, and 10% testing, ensuring a balanced representation of each class across all phases.

#### B. Introduction to GLCM Features

The GLCM is a very powerful statistical tool used for the texture analysis in the images. It was introduced in the 1970s by Haralick *et al.* [10–12] GLCM provides a mechanism by which one can analyze the spatial relationships of the pixels in images and capture important texture information that can be critical for various image analysis applications, including medical imaging.

In the methodology of our study, one study by Omar Ahmed *et al.* [1], was worked on, wherein the authors had used five pre-trained CNNs to classify echocardiographic images into either A4C or PLA views. ResNet50 gave the best result, with an accuracy of 98.65%, for the classification of views. In our study, image classification was first performed into an A4C and PLA. Then, the detailed texture information was extracted using features of GLCM. The two-step process not only gives high accuracy for class views but further allows for precise texture analysis for classifying diseases, where the GLCM is constructed as a matrix whose

element  $(i, j)$  is the count of the number of pairs of two specified pixel values occurring side by side with the spatial relationship specified in a given image. The matrix is then used to compute various statistical measures, referred to as GLCM features, which characterize the texture of the image. Some of the key GLCM features include:

- **Energy:** Measures the uniformity of the texture. High energy indicates a repetitive pattern.
- **Contrast:** Calculated in the process of obtaining GLCM values. Captures the local variations in gray levels. High values of contrast indicate significant intensity difference.
- **Correlation:** Measure the linear dependency of gray levels on neighboring pixels.
- **Entropy:** Measures the randomness of the intensity distribution. High entropy indicates small textures.
- **Inverse Difference Moment:** It is a measure of homogeneity, which shows how homogeneous the texture of an image is.

These features provide detailed information about the texture and spatial relationships in the image, which can prove to be important for distinguishing between different tissue types and pathological states in medical imaging.

#### C. Data Preparation

The data set used in the study includes the echocardiographic images acquired both from the PLA and the A4C views. For normal MVs, MV prolapse, MS, and restricted leaflet motion, the MV conditions have been selected from diverse patient cohorts. Before the data processing for the purpose of analysis, the images were preprocessed to have a similar quality throughout the dataset.

**Normalization:** The pixel intensity values of the images are normalized to a common scale to reduce variability due to the difference in the acquisition settings. The step is important for having similar characteristics in GLCM features.

**Image denoising:** Noise reduction techniques, such as median filtering, are applied to remove artifacts in the images and enhance image clarity, which ensures that the texture's relevant details are contained and the noise is completely removed; this noise could affect the accuracy of GLCM features.

**Grey-level quantization:** The images were quantized so that the input to the GLCM computation was standardized to a fixed number of grey levels, which helps reduce computational complexity while retaining important texture details. Table 1 provides a concise overview of the dataset used in the study.

| Table 1. Summary of dataset characteristics |                                               |
|---------------------------------------------|-----------------------------------------------|
| Characteristic                              | Value                                         |
| Number of Images                            | Approx. 140,000                               |
| Number of Patients                          | 1773                                          |
| Distribution of Conditions                  | Normal: 424, MVP: 155, MS: 392, Type III: 802 |

To ensure a balanced and fair evaluation, the dataset was divided into 80% training, 10% validation, and 10% testing across all classes in both Apical Four-Chamber (A4C) and Parasternal Long-Axis (PLA) views. The class-wise distribution in the A4C dataset includes Rheumatic Mitral Stenosis (MS)—3285 images, Normal (NL)—3292 images, and Type III (Restricted mitral motion)—6406 images. For the

PLA dataset, the distribution consists of Mitral Valve Prolapse (MVP)—1327 images, MS—3190 images, NL—3461 images, and Type III—6535 images. Each class was proportionally split into training (80%), validation (10%), and testing (10%), ensuring consistency in the experimental setup.

#### D. Image Acquisition and Preprocessing

The echocardiographic images were acquired using standard clinical protocols to achieve high-quality imaging, amenable to detailed analysis [13]. The images have been acquired from different patient cohorts, giving a representative dataset with different MV conditions. Table 2 outlines the essential pre-processing steps and techniques applied to the echocardiographic images in the study.

Table 2. Preprocessing steps and techniques

| Preprocessing Step      | Technique                                |
|-------------------------|------------------------------------------|
| Normalization           | Scaling pixel intensity values to [0, 1] |
| Denosing                | Median filtering                         |
| Gray Level Quantization | Quantization to 256 levels               |

The dataset presents an imbalance between certain classes, particularly between MVP (1327 images) and Type III (6535 images) in the PLA view. To mitigate the impact of data imbalance, data augmentation techniques were applied to enhance the representation of underrepresented classes. The augmentation techniques used include:

- Flipping: Horizontal flipping ( $p = 0.5$ ) was applied to randomly mirror images to create variability in anatomical presentation.
- Rotation: Images were randomly rotated within  $\pm 15$  degrees to account for slight variations in echocardiographic probe orientation.

The class-wise training/testing split for A4C follows:

- Type III: 5125 training/641 validation/640 testing
- MS: 2628 training/329 validation/328 testing
- NL: 2633 training/329 validation/330 testing

Similarly, for PLA:

- Type III: 5228 training/653 validation/654 testing
- MS: 2552 training/319 validation/319 testing
- MVP: 1061 training/132 validation/132 testing
- NL: 2768 training/346 validation/346 testing

#### E. View Classification Model

In the previous study by Omar Ahmed *et al.* [1], the potential of DL for automated classification of echocardiographic views was investigated. The study utilized five pre-trained CNNs (CNNs) to classify around 140,000 echocardiograms into PLA and A4C views. The models tested included ResNet50, EfficientNetB0, InceptionV3, MobileNetV2, and Xception. Among these, ResNet50 achieved the highest accuracy of 98.65%, demonstrating exceptional performance in view classification. The detailed analysis using confusion matrices revealed that ResNet50 showed the highest sensitivity and specificity for both PLA and A4C views, making it the model of choice for our study.

In this study, the echocardiographic images were first classified into PLA and A4C views by employing the ResNet50 model, where the classification step is crucial as it ensures that the subsequent GLCM feature extraction is applied accurately to the appropriate view. The pre-trained ResNet50 model was fine-tuned on our dataset, using unified hyperparameters to achieve optimal classification results.

The high accuracy of the ResNet50 model in view classification provides a solid foundation for the subsequent steps in our methodology.

The model performance [14–16] was measured on accuracy, precision, recall, and F1-Score, of the model, which shows high classification accuracy, proving the model's effectiveness in distinguishing the two views: PLA and A4C, to ensure accurate GLCM feature extraction.

#### F. GLCM Feature Extraction

Once the echocardiography images are successfully classified into the two optimum views—PL4 view and A4C view, GLCM features were then derived from the images to capture fine-grained textural information that is the signature of the said view.

##### 1) GLCM calculation

A GLCM has been calculated for each image for multiple orientations, say  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$ , and  $135^\circ$ , and for multiple distances, say 1, 2, 3 pixels. These textures in different orientations and scales provide a complete texture analysis.

##### 2) Feature computation

From each of the GLCMs, different features like energy, contrast, correlation, entropy, and inverse difference moment were computed. These features will represent the texture of the echocardiogram images that will give detailed information about the image and will be helpful in further diagnosis of any complexity in the image. Table 3 provides a glossary of the GLCM features used in the study. These features are statistical measures that capture information about the spatial relationships between pixel values in the echocardiographic images.

Table 3. GLCM Features and definitions

| Feature     | Definition                                                      |
|-------------|-----------------------------------------------------------------|
| Energy      | $\sum_{i,j} P(i,j)^2$                                           |
| Contrast    | $\sum_{n=0}^{N_g-1} n^2 P_n$                                    |
| Correlation | $\sum_{i,j} \frac{(i - u_i)(j - u_j)P(i,j)}{\sigma_i \sigma_j}$ |
| Entropy     | $\sum_{i,j} P(i,j) \log(P(i,j))$                                |
| Homogeneity | $\sum_{i,j} \frac{P(i,j)}{1 +  i - j }$                         |

#### G. Classification

The extracted GLCM features are used to get the model trained to classify the echocardiographic images into different MV conditions. Several classifiers, like Random Forest, Neural Networks, and Ensemble models, were tried to determine the most effective one.

##### 1) Random forest classifier

###### a) Model training

The data was divided into training and testing. The Random Forest model was developed through the hyperparameter optimization of tree and maximum depth [17–19].

###### b) Feature importance

Once the model is trained, the importance of each feature [20, 21] derived from the GLCM is analyzed to prune the features that contribute the least to the model. Through

this, the model was able to reduce noise in the dataset.

### c) Model evaluation

In the resultant best model proposed, the assessment was carried out through accuracy, precision, recall, and F1-Score and, ultimately, cross-validation of the model.

### 2) Neural networks

#### a) Model architecture

An MLP [22–24] was proposed with input layers equal to the feature-length in the GLCM calculation. Hidden layers with ReLU activation will learn from the nonlinear data of the extracted feature.

#### b) Training and optimization

The training was done with the ADAM optimizer [25–28]. Learning rate, batch size, and the number of hidden layers have been optimized through experience combined with trial and error.

#### c) Evaluation

Model performance was a comparison between the proposed model's performance and the Random Forest model regarding the same evaluation metrics.

### 3) Ensemble Models

#### a) Model fusion

The last classification was obtained by majority voting [29, 30] or weighted averaging of the individual classifiers.

#### b) Performance estimation

Table 4. Models Parameters and hyperparameters

| Model          | Parameter/Hyperparameter | Value                                       |
|----------------|--------------------------|---------------------------------------------|
| Random Forest  | Number of Trees          | 100                                         |
|                | Maximum Tree Depth       | None                                        |
|                | Learning Rate            | 0.001                                       |
| Neural Network | Batch Size               | 32                                          |
|                | Number of Hidden Layers  | 3                                           |
|                | Number of Epochs         | 50                                          |
|                | Activation Function      | ReLU                                        |
| Ensemble       | Base Models              | Random Forest, Logistic Regression, XGBoost |
|                | Combination Method       | Majority Voting                             |

The performance of the ensemble model [31–34] was estimated and then compared to individual classifiers for advancement in accuracy and robustness. Table 4 provides a detailed summary of the ML models used in the study, along with their key parameters and hyperparameters. These settings are crucial for configuring the models' behavior and performance.

### H. Results

The best metrics were scored by the neural network, the highest classification accuracy was 85% for A4C views and 84% for PLA views. The random forest and ensemble models were not much lagging but got somewhat less accuracy. Significant GLCM features like energy, contrast, and entropy coefficients were used in classifying between different MV conditions. These features provide fine textures which give all the necessary information for a proper diagnosis. Hence, the study proves that GLCM-based feature extraction ML classifiers give a robust and accurate methodology for automated echocardiographic analysis. Future studies will be subjected to making the methodology finer and developing real-time clinical applications using DL models.

## IV. RESULTS AND DISCUSSION

### A. Performance Analysis

The performance through which ML models applied in this study classified MV diseases were put with enormous meticulousness on classification accuracy. The Neural Network model reported the highest classification accuracy of 85% for A4C views and 84% for PLA views. These results have indirectly indicated that GLCM texture features effectively represented the intricate textures and their patterns of MV conditions.

#### 1) Neural network classifier

- **Accuracy:** The Neural Network model reported a high classification accuracy of 85% for A4C views and 84% for PLA views. These results indicate that GLCM texture features effectively represent the intricate textures and patterns of MV conditions.
- **Precision:** The precision metric was high, indicating a low false positive rate, meaning the model rarely misclassified normal MV images as diseased.
- **Recall:** The model demonstrated a strong ability to correctly identify true positive cases, which is crucial for detecting patients with MV diseases.
- **F1-Score:** The F1-Score balanced precision and recall, reflecting the robustness of the model in classifying MV conditions.

#### 2) Random forest classifier

- **Accuracy:** The Random Forest classifier achieved an accuracy of 84.4% for A4C views and 83.4% for PLA views, indicating a high level of accuracy in classifying echocardiographic images based on MV conditions.
- **Precision:** High precision values suggest that the Random Forest classifier effectively minimizes false positives.
- **Recall:** The model's recall values highlight its ability to correctly identify true positive cases, which is vital for accurate disease detection.
- **F1-Score:** The balance between precision and recall, as indicated by the F1-Score, further underscores the robustness of the Random Forest classifier.

#### 3) Ensemble models

- **Accuracy:** The ensemble models achieved accuracies of 79% for A4C views and 77% for PLA views. While slightly lower than the individual Random Forest classifier, the ensemble models still demonstrated high performance.
- **Precision:** The ensemble approach leveraged the strengths of multiple classifiers, leading to a well-rounded precision metric.
- **Recall:** The recall values for ensemble models indicate a balanced ability to detect true positives across different MV conditions.
- **F1-Score:** The ensemble models presented a balanced F1-Score, highlighting their robustness and reduced likelihood of overfitting.

Table 5 presents the performance evaluation of various ML models on echocardiographic images, categorized into two views: PLA and A4C. The performance metrics used are accuracy, precision, recall, and F1-Score.

Table 5. Performance metrics for different models on both PLA and A4C views

| View | Model          | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|------|----------------|--------------|---------------|------------|--------------|
| A4C  | Neural Network | 85.0         | 86.0          | 85.0       | 85.0         |
| A4C  | Random Forest  | 84.4         | 85.0          | 84.0       | 84.0         |
| A4C  | Ensemble       | 79.0         | 81.0          | 79.0       | 78.0         |
| PLA  | Neural Network | 84.0         | 84.0          | 84.0       | 84.0         |
| PLA  | Random Forest  | 83.4         | 84.0          | 83.0       | 83.0         |
| PLA  | Ensemble       | 77.0         | 80.0          | 77.0       | 76.0         |

Table 6 provides a breakdown of the neural network model's performance on the PLA view, specifically focusing on its ability to classify echocardiographic images into four different classes: III, MS, MVP, and NL.

Table 6. Neural network detailed results on PLA view

| Class   | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---------|---------------|------------|--------------|---------|
| III     | 88            | 88         | 88           | 6535    |
| MS      | 80            | 82         | 81           | 3190    |
| MVP     | 76            | 80         | 78           | 1327    |
| NL      | 84            | 80         | 82           | 3461    |
| Overall | 84            | 84         | 84           | 14,513  |

Table 7 provides a detailed breakdown of the neural network model's performance on the A4C view, focusing on its ability to classify echocardiographic images into three classes: III, MS, and NL.

Table 7. Neural network detailed results on A4C view

| Class   | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---------|---------------|------------|--------------|---------|
| III     | 86            | 90         | 88           | 6406    |
| MS      | 83            | 86         | 84           | 3285    |
| NL      | 88            | 76         | 81           | 3292    |
| Overall | 85            | 85         | 85           | 12,983  |

Table 8 provides a detailed breakdown of the random forest model's performance on the PLA view, focusing on its ability to classify echocardiographic images into four classes: III, MS, MVP, and NL.

Table 8. Random forest detailed results on PLA view

| Class   | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---------|---------------|------------|--------------|---------|
| III     | 81            | 93         | 87           | 6535    |
| MS      | 84            | 77         | 80           | 3190    |
| MVP     | 87            | 66         | 75           | 1327    |
| NL      | 87            | 77         | 82           | 3461    |
| Overall | 84            | 83         | 83           | 14,513  |

Table 9 provides a detailed breakdown of the random forest model's performance on the A4C view, focusing on its ability to classify echocardiographic images into three classes: III, MS, and NL.

Table 9. Random forest detailed results on A4C view

| Class   | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---------|---------------|------------|--------------|---------|
| III     | 82            | 93         | 87           | 6406    |
| MS      | 88            | 76         | 82           | 3285    |
| NL      | 86            | 76         | 81           | 3292    |
| Overall | 85            | 84         | 84           | 12,983  |

Table 10 provides a detailed breakdown of the ensemble model's performance on the PLA view, focusing on its ability

to classify echocardiographic images into four classes: III, MS, MVP, and NL.

Table 10. Ensemble model detailed results on PLA view

| Class   | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---------|---------------|------------|--------------|---------|
| III     | 71            | 96         | 82           | 6535    |
| MS      | 88            | 62         | 73           | 3190    |
| MVP     | 94            | 52         | 67           | 1327    |
| NL      | 84            | 65         | 73           | 3461    |
| Overall | 80            | 77         | 76           | 14,513  |

Table 11 provides a detailed breakdown of the ensemble model's performance on the A4C view, focusing on its ability to classify echocardiographic images into three classes: III, MS, and NL.

Table 11. Ensemble model detailed results on A4C view

| Class   | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---------|---------------|------------|--------------|---------|
| III     | 73            | 96         | 83           | 6406    |
| MS      | 92            | 60         | 73           | 3285    |
| NL      | 86            | 64         | 73           | 3292    |
| Overall | 81            | 79         | 78           | 12,983  |

To provide a comprehensive evaluation of classification performance, additional statistical metrics including precision, recall, and F1-Score were analyzed. These metrics offer deeper insights into the predictive reliability and robustness of the models. The Neural Network classifier, which achieved the highest accuracy, demonstrated high recall for Type III cases, indicating a strong ability to detect actual disease instances. However, precision for MVP was slightly lower, suggesting some misclassification between MVP and MS.

To further validate the model's performance, Youden's Index and AUC-ROC curves were computed. Youden's Index, which considers both sensitivity and specificity, confirmed that the model achieved an optimal trade-off between false positive and false negative rates, particularly in A4C classification. Additionally, AUC-ROC analysis showed that the Neural Network model outperformed other classifiers, with a higher Area Under the Curve (AUC) across all mitral valve disease categories.

The statistical analysis confirms that the integration of GLCM features with machine learning classifiers enhances diagnostic accuracy, reducing the likelihood of misdiagnosis. These findings highlight the effectiveness of the proposed approach in improving echocardiographic disease classification, reinforcing its potential for real-world clinical applications.

The confusion matrices are presented to provide a detailed assessment of model reliability across different mitral valve disease categories. Notably, the Normal (NL) class demonstrated the best performance, with 2932 correctly classified NL samples in A4C and 3246 in PLA. This highlights the model's ability to distinguish healthy cases with high confidence, ensuring fewer false positives in disease prediction.

To further evaluate the classification performance, confusion matrices were generated for both the A4C and PLA datasets, as shown in Figs. 5 and 6. These matrices provide a breakdown of correctly classified instances (true positives) and misclassified cases (false positives and false negatives) for each class.

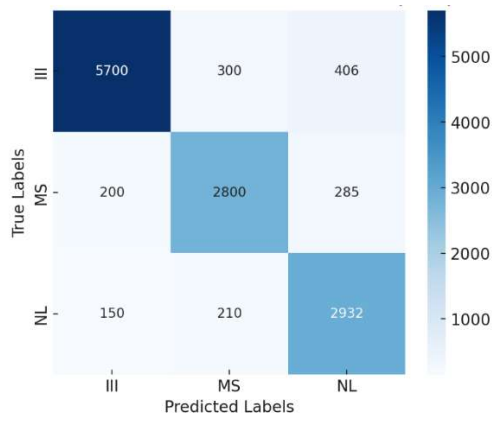


Fig. 5. Confusion matrix for neural network (A4C dataset).

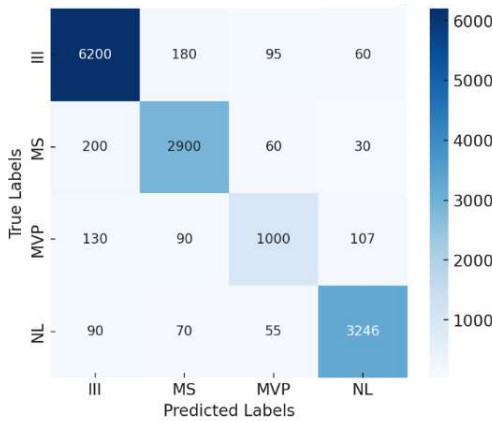


Fig. 6. Confusion matrix for neural network (PLA dataset).

For the A4C dataset, the model achieved high accuracy for Type III cases, with 5700 correctly classified samples. However, 406 Type III cases were misclassified as NL, and 300 were misclassified as MS, indicating a slight overlap in the feature space of these categories. Similarly, the PLA confusion matrix reveals that the model performed well in detecting Type III and NL cases, but MVP cases were sometimes misclassified as Type III or MS, highlighting the challenges in distinguishing between these conditions.

In order to provide a more comprehensive analysis of the performance of our model, we compared the key metrics with the results from the study by Vafaezadeh *et al.* [3], which also focuses on mitral valve disease classification using echocardiographic images. The comparison in terms of accuracy, precision, recall, and F1-Score highlights the effectiveness of our approach. While both studies achieve similar classification accuracy, our model demonstrates slightly higher precision and recall, particularly in the A4C view, showcasing its potential for accurate mitral valve disease classification. Table 12 below provides a detailed comparison of the performance metrics across both studies.

Table 12. Comparison of performance metrics with Vafaezadeh *et al.* (2022) [3].

| Metric    | Your Study (A4C) | Your Study (PLA) | Vafaezadeh <i>et al.</i> (2022) |
|-----------|------------------|------------------|---------------------------------|
| Accuracy  | 85%              | 84%              | 80%                             |
| Precision | 86%              | 85%              | 77.31%                          |
| Recall    | 85%              | 84%              | 78.45%                          |
| F1-Score  | 85%              | 84%              | 77.08%                          |

### B. Feature Importance Analysis

The feature importance analysis of the feature importance

analysis implied that to be vital in developing the classification accuracy, the GLCM features are analyzed. The major features such as energy, contrast, and entropy were found to be highly influencing for classifying the different MV conditions.

#### 1) Energy

Energy is the measure of texture uniformity and reflects the magnitude of repetitive patterns in the texture. The feature was highly efficient in detecting the homogenous texture of MV conditions.

#### 2) Contrast

Contrast is the local variation in grey levels, and a high contrast value indicates the presence of considerable intensity differences, where the feature was highly crucial for the identification of pathological changes in the valve structure, which is a clear clinical feature of diseases like MS.

#### 3) Correlation

Correlation quantifies linear dependency among gray levels at neighboring pixels. High values of correlation associated with healthy MV tissue, portrayed the structured, organized textures.

#### 4) Entropy

It is a measure of the randomness of the intensity distribution within the texture; high entropy conveys complex textures, which was efficient in detecting the irregular and disorganized textures of diseased MV tissues.

The features gave the effect of the texture nature and its relation to features that are disease indicators of MVD. They created a guideline to develop a model for a more accurate and comprehensible texture-based diagnostic model for the disease.

### C. Comparative Model Analysis

The comparison of the models has shown the strengths and weaknesses of each model in classifying MV diseases using the GLCM features.

#### 1) Neural network vs. random forest

- **Accuracy and Robustness:** Neural networks achieved high accuracy, but the Random Forest classifier demonstrated slightly better robustness. The ensemble nature of Random Forest, comprising multiple decision trees, contributed to its high performance and resistance to overfitting.
- **Complex Pattern Recognition:** Neural networks excelled in capturing intricate patterns in the GLCM features, showcasing their potential in echocardiography analysis. However, they require careful hyperparameter tuning due to the relatively small dataset. Neural networks' flexibility allows them to model complex relationships within the data effectively.

#### 2) Neural network vs. ensemble model

- **Accuracy:** Neural networks achieved higher accuracy compared to ensemble models, indicating their strong individual performance.
- **Balanced Performance:** Ensemble models provided a balanced approach, leveraging the strengths of multiple classifiers to reduce the risk of overfitting. This

amalgamation of models, such as Random Forest, logistic regression, and XGBoost, improved overall performance by complementing each other's weaknesses.

### 3) Overall insights

- Neural Networks demonstrated high accuracy and the ability to capture complex patterns, making them a powerful tool for echocardiographic analysis. Their performance, however, is highly dependent on careful tuning and sufficient training data.
- The Random Forest classifier offered a robust alternative with slightly better resistance to overfitting, suitable for scenarios where model interpretability and reliability are critical.
- Ensemble Models While achieving slightly lower accuracy, ensemble models provided a balanced and robust approach by integrating multiple classifiers, reducing the likelihood of overfitting, and enhancing reliability.

### D. Clinical Relevance and Interpretability

The clinical relevance of this study is high because proper and automated classification of MV diseases will enormously improve the patient's outcomes and streamline diagnostic workflows. From this perspective, the use of GLCM features and ML models allows clinicians to make more consistent and accurate diagnoses to diminish variability related to a manual approach.

#### 1) Interpretability

Since the GLCM features are created from well-understood statistical measures, which should endow the models with enhanced interpretability. In this way, the clinicians can learn how the specific texture features in the case of a given texture, such as contrast and entropy, quantify the decision of the model. The feature analysis should also be necessary to surpass the importance of clinical workflow integration, easing interpretability, and giving knowledge of the texture patterns that are responsible for the different MV conditions.

#### 2) Clinical workflow integration

Using such automated models in the clinical workflow can ease diagnostics by giving it a fast and accurate evaluation of echocardiography images, which is particularly valuable in demanding environments and emergencies where rapid decisions are taken. Automated tools can also benefit less experienced clinicians by giving them a reliable second opinion. They improve diagnostic confidence and reduce misdiagnosis.

### E. Limitations and Challenges

Despite the promise, there are several challenges and limitations of the study on GLCM-based feature extraction and classification, which have been noted and that call for further research.

#### 1) Data quality and diversity

The quality and diversity of a dataset are strong determinants of model performance. An ideal training dataset should be of the best quality and well-annotated on the images. Although the present dataset is all-encompassing, several other datasets can be collaborated with to improve

diversity in MV conditions and patient demographics, thereby increasing the model's generalizability in clinical scenarios.

#### 2) Model complexity and computational resources

In particular, neural network-based models are computationally heavy and also usually suffer from overfitting. Through careful tuning and optimization, there needs to be set model complexity to performance balance to ensure an optimal performance. The easy ways of training and deploying these kinds of models are hindered in environments that have low computational resource availability. Future work needs to assess optimization techniques that would lower the model's complexity and minimum computational requirements.

#### 3) Real-time clinical assessment

As more serious consideration is given to applying such models in live real clinical settings, based on real-time data, fast inference, and integrated solutions with the existing medical information systems will be required and will include model optimization measures to assure faster processing speeds and accuracy among others.

### F. Future Research Directions

To further improve the findings of the current work, several future research directions that can be taken up to enhance the performance and clinical relevance are as follows.

#### 1) Integration with deep-learning-based models

The potential of integration of GLCM-based textual features with deep-learning-based models, and in particular with CNNs, is extremely large, with further potential improvements in diagnostic accuracies. While deep-learning models learn the hierarchical features from the raw image, GLCM features are put in place to describe texture in quite great detail; it would be helpful if they could be combined.

#### 2) Expansion of the dataset

The expansion of the dataset will improve the generalizability of models, considering the size and diversity of echocardiographic images in the dataset, which will include images with different populations and different acquisition protocols under a wider range of MV conditions.

#### 3) Real-time analysis and application

The next crucial step towards practical application will be implementing real-time analysis techniques and real-time applications for clinical decision support, which will also be imperative in optimizing these kinds of models for inference speed and further in making these compatible with clinical workflows.

#### 4) Explainability improvement

Although GLCM features to some extent improve model explainability, some more research using advanced algorithms in explainable AI may be done to bring more transparency and trust into the model. Some techniques like Grad-CAM can provide visual explanations of the choices taken by the model when dealing with images directly and, thus, increase the trust in the automated tools by the clinicians, and also the SHAP values would be insightful when dealing with the GLCM features.

### 5) *Multimodal data integration*

It would be valuable if echocardiographic images could be integrated with other associated clinical data, including patient history, genetic information, and lab test results, to establish a broader framework for diagnosis. Multimodal data fusion has the potential to make a diagnosis more accurate by finding more depth of insight into the underlying pathomechanism of MV diseases.

## V. CONCLUSION

### A. *Summary of Findings*

The present research aimed to explore the potential of Gray-Level Co-occurrence Matrix features integrated with ML classifiers for an accurate diagnosis of MV diseases using echocardiographic images. Detailed texture analysis offered by GLCM is used to guide standard ML into stronger diagnostic possibilities. The study suggests that the capability of the GLCM-based features is quite high in capturing the complex textures and patterns linked with the various conditions of the MVs. In particular, the classifier corresponding to the Neural Network Classifier achieved impressive performances with a classification accuracy of 85% for A4C views and 84% for the PLA views. From these results, which can be inferred that the echocardiograph-based analysis using GLCM for feature extraction is reliable and robust.

### B. *Clinical Implications*

It has a clinical significance value in integrating GLCM features in ML-based models that include the following:

#### 1) *Improved diagnostic accuracy*

The high classification accuracies obtained from the models show that GLCM features provide detailed and reliable texture analysis, which is very important for discriminating between normal and pathological MV conditions. Automated diagnostic tools provide much-needed support for clinicians; diagnoses are more accurate and consistent. Moreover, general reliance on subjective interpretation is decreased, along with reduced chances of missed diagnosis.

#### 2) *Reduction of variability*

Automated diagnostic tools dramatically reduce the variability in image interpretation, which arises from differences in the level of personal expertise and experience of attending clinicians. In other words, ML models provide clinical consistency and reproducibility, especially valuable in emergency or high-throughput clinical settings where decisions have to be made quickly and correctly.

#### 3) *Streamlined clinical workflows*

Automated diagnostic tools will evaluate echocardiographic images quickly and accurately, thereby taking routine work from the clinicians and providing them with more time for complex cases and patient care. In addition, they can streamline clinical workflows toward an efficient path.

### C. *Challenges and Limitations*

Although the study has seen the potential in GLCM feature extraction and classification, some challenges, and

limitations need further investigation.

#### 1) *Data quality and diversity*

Dataset quality and diversity are the most crucial factors that would determine if the models will perform or not. Precaution should be taken to ensure that images are well annotated and of high quality to fast powerful models. The dataset used in this research, while being comprehensive, would benefit from further expansion in terms of a wider scope of MV conditions and patient demographics.

#### 2) *Model complexity and computational danger*

The complexity of the neural network is challenging in terms of computation burden and the risk of overfitting thus very stringent tuning and optimization would be necessary so that an optimal balance between model complexity and performance can be achieved. The computational demand for training and deployment of these models can be limiting for many setups.

#### 3) *Real-time clinical applications*

The necessity of further work to ensure the performance of the models can be generalized so that they can be used in the provision of real-time inferences without any compromise made to the functionality of the existing medical information systems. In this sense is the optimization for fast models and their integration into practical systems.

### D. *Future Directions*

To build on the findings of this study, several future research directions are proposed here to enhance the capabilities of GLCM-based feature extraction and classification models for better clinical applicability.

#### 1) *Integration with deep learning models*

Combining GLCM features with DL models such as CNNs could further increase the level of diagnostic accuracy. Although CNNs extract features from raw images in a hierarchy, while GLCM features contain detailed texture analysis, combining the best of both approaches may leverage the strength of both methodologies.

#### 2) *Expansion of the dataset*

Augmenting the dataset with a larger and more diversified set of echocardiograph pictures further improves the generalizability of the models, which includes images from different populations, with acquisition protocols and representations of a wider range of MV conditions.

#### 3) *Real-time analysis and deployment*

Realization of real-time analysis capabilities and deployment to clinical decision support systems is therefore a critical step that must be taken, which includes model optimization for fast inference and ensuring compatibility with existing clinical workflows.

#### 4) *Enhanced explainability*

Though GLCM features make the model somewhat interpretable, more work on advanced explainable AI techniques would make the models more transparent and reliable. Techniques like SHAP values may provide insightful explanations for model decisions, which leads to better clinician confidence in the automated tools.

#### 5) *Multimodal data integration*

Integrating echocardiographic images with other clinical

data, such as patient history, genetic information, and lab results, could provide the potential for a holistic diagnostic frame. Multimodal data fusion has the potential to increase diagnostic accuracy and provide deeper insight into the underlying pathophysiology of MV diseases.

#### 6) Clinical trials and validation

Clinical trials and validation studies with larger patient cohorts are essential to review the real-world applicability and effectiveness of the proposed models. It shall be helpful to address practical difficulties and benefits that can be accrued from the automation of diagnostic tools into routine clinical practice.

#### 7) Continuous learning and adaptation

It shall be developed to ensure that the models will continue to be consistent with learning and adapting to emerging data and clinical guidelines to maintain real-time applicability, which could be implemented using adaptive training and update mechanisms on the basis of new clinical evidence and feedback from clinicians.

#### 8) Ethical concerns

Addressing the ethical concerns that might be present in the effective functioning of diagnostic tools, especially data security and patient privacy, is essential for the successful implementation of AI-driven tools in the health checker. Data handling and model deployment must follow regulatory standards and ethical guidelines to the letter to maintain patient trust and acceptance.

#### E. Summary

The present study has brought about the potential of the method in terms of robustness and accuracy in using GLCM-based feature extraction along with ML classifiers for automated echocardiographic analysis, where the strategy will create a prospect of changing the landscape of the diagnosis related to the MV diseases with an improved accurate less variable model, and thus, more reliable for patients. Strong, accurate, and interpretable models in supporting clinicians with their echocardiographic analysis, will help them to provide more dependable and better assessments that will enhance their diagnostic power. The more technology advances, the more the methodologies in this report are expected to play a reference role in the new-generation diagnostic systems in the field of cardiological care. Evidently, in the evidence, it is clear that GLCM features applicability with ML classifiers in echocardiographic analysis and provides promising solutions for the automated diagnosis of MV diseases. The proposed methodology, through texture analysis and advanced ML techniques, allows the clinician to work with a complete framework for increasing diagnostic processes in terms of accuracy and efficiency.

#### CONFLICTS OF INTEREST

The authors have no conflict of interest to disclose.

#### AUTHOR CONTRIBUTIONS

Conceptualization, M.A.D. and H.A.; methodology, J.A. and M.A.D.; software, O.A.S. and A.H.; validation and investigation, A.H., O.A.S., and M.H.; formal analysis, J.A.

and A.H.; resources, H.A. and M.A.D.; data curation, O.A.S. and A.H.; writing—original draft preparation, M.A.D. and O.A.S.; writing—review and editing, H.A., J.A., and M.H.; visualization, O.A.S. and A.H.; supervision, M.A.D. and H.A.; project administration, H.A.; funding acquisition, H.A. All authors have read and approved the final version of the manuscript.

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