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DeepSTEMI: Artificial Intelligent Support System for Rapid Diagnosis and Treatment of ST-segment elevation Myocardial Infarction in Pre-hospital Emergency Medical Services at SRCA In Makkah Al-Mukarramah

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Abstract. this research addresses the critical imperative for improved cardiac care in pre-hospital emergency services through the integration of an artificial intelligence (AI) based diagnostic system. A survey involving 237 participants in Saudi Arabia illuminates the essential need to minimize on-site duration during cardiac emergencies, with unanimous agreement among participants regarding the pivotal role of AI in expediting responses, also demographic analysis provides valuable insights into participant trends, contributing to a comprehensive background understanding. The study proposes a methodological pipeline that encompasses key elements, including data augmentation, ResNet50 model training, and the development of a user-friendly AI assistant named DeepSTEMI. This AI assistant is designed to predict specifically ST-segment elevation myocardial infarction (STEMI) from given images and respond to initial treatment. Demonstrating robust binary classification performance, the ResNet50 model consistently exhibits high precision, recall, F1-score, and accuracy. A validated area under the curve (AUC) score of 0.98 underscores the model's discriminative prowess in distinguishing STEMI from normal cases. Emphasizing practical strategies, the study advocates for collaboration with the Saudi Red Crescent Authority, continuous model refinement, and system expansion to address a broader spectrum of cardiac conditions. Furthermore, the research highlights the importance of integrating real-time data feeds and incorporating continuous learning as pivotal elements to enhance diagnostic precision.

ST-segment elevation myocardial infarction, Saudi Red Crescent Authority, pre-hospital emergency services, Deep learning, Makkah Al-Mukarramah

I. INTRODUCTION

Every year, millions of Muslims from around the world con- verge in Makkah, Saudi Arabia, to embark on the significant pil- grimage of Hajj [1]. This spiritual journey demands considerable physical effort, and research indicates that attendees experience various communicable and non-communicable diseases. Notably, cardiovascular diseases (CVDs) have been identified as the pri- mary cause of mortality among Hajj participants [2]. The global prevalence of CVDs is on the rise, overtaking cancer and claiming approximately 17.3 million lives annually [3]. Projections from the World Health Organization (WHO) estimate a further increase to 23.6 million CVD-related deaths by 2030, emphasizing the ur- gency of addressing this growing health concern [4].

Among CVDs, myocardial infarction (MI) and stroke con- tribute to a significant portion of cardiovascular-related fatalities [5]. MI, commonly known as a heart attack, can manifest as ST- segment elevation myocardial infarction (STEMI), involving the complete blockage of a coronary artery [6]. Lifestyle choices such as poor eating habits, inactivity, and stress are closely asso- ciated with coronary artery diseases, underscoring the importance of early diagnosis and intervention [7]. Clinical signs of MI in- clude chest pain and difficulty breathing [8]. However, accurate diagnosis requires more than just the observation of symptoms, as they may not be sensitive or specific enough.

In acute settings, early diagnosis is paramount, with electrocar- diogram (ECG) and cardiac enzymes serving as pivotal diagnostic tools, particularly in severe cases like STEMI [9]. While enzymes may lack prompt elevation in STEMI, ECG signals, reflecting the heart’s electrical activity, offer valuable insights as a frontline di- agnostic approach [10, 11]. However, manual ECG interpretation poses challenges, especially in scenarios lacking immediate medi- cal expertise, such as emergencies or remote locations like the Hajj pilgrimage [2]. Addressing this, a growing body of research fo- cuses on leveraging artificial intelligence (AI) for clinical decision support systems in MI diagnosis [7], aiming to enhance accuracy and efficiency, particularly in the less-explored area of STEMI.

The primary objective of the research is to significantly re- duce on-site duration in assessing and managing ECG readings, specifically targeting potential heart attacks like STEMI [12]. The current reliance on manual interpretation by Red Crescent profes- sionals leads to delays in coordinating with hospitals for patient admission [13]. The proposed solution involves integrating an AI algorithm for rapid ECG analysis, immediate treatment recommen- dations, and notifications to nearby hospitals equipped with cardiac catheterization facilities. This innovative approach ensures prompt evaluation and acceptance or rejection of cases based on hospital availability, streamlining the entire process for a continuous and efficient workflow.

This research makes a substantial contribution to advancing pre-hospital emergency cardiac care, particularly during the Hajj pilgrimage. By comprehensively understanding health challenges and focusing on STEMI, this study aims to enhance early diagno- sis and intervention. Addressing challenges in ECG image inter- pretation, and explore innovative AI solutions to predict STEMI, aiming to reduce on-site duration and streamline hospital coordina- tion. Additionally, the collaboration with the Saudi Red Crescent Authority, continuous model refinement, and system expansion underscore our commitment to addressing a broader spectrum of cardiac conditions. The integration of real-time data feeds and continuous learning emerges as pivotal elements, enhancing diag- nostic precision in pre-hospital emergency settings.

A Research question

- How can we effectively reduce the mortality rate due to CVD, specifically focusing on STEMI, among participants in the Hajj pilgrimage and in other medical emergencies?
- What role can artificial intelligence play in overcoming chal- lenges related to ECG

interpretation during emergency situa- tions?

• How does the integration of real-time data feeds and contin- uous learning contribute to enhancing diagnostic precision in pre-hospital emergency cardiac care?

The article's structure unfolds as follows: Section 2 delves into an extensive background of the study, setting the foundation for understanding. Section 3 elucidates the research methodology, encompassing the AI model and survey design. Following this, Section 4 engages in analysis and discussion. Ultimately, Section 5 draws the paper to a close, encapsulating major recommendations, contributions, limitations, and areas earmarked for improvement.

II. BACKGROUND STUDY

In the pursuit of enhancing myocardial infarction (MI) detec- tion, Tadesse et al. present a groundbreaking multi-lead fusion approach [14]. Their primary objective is not only to identify the presence of MI but also to predict its occurrence time. To achieve this, they leverage the GGH dataset, specifically focusing on ECG data. The innovative aspect of their methodology lies in data fusion, where information from multiple leads is seam- lessly integrated. Employing a Dense-Long Short-Term Memory (Dense-LSTM) architecture, the researchers evaluate their model using a comprehensive set of metrics, including AUROC, accu- racy, precision, sensitivity, specificity, and f-1 score. The results are remarkable, with AUROCs ranging from 96.7% to 73.8%, showcasing the efficacy of their multi-lead fusion approach in MI detection.

Chen and his team contribute to the field with an innovative neural network (NN) algorithm designed for the automatic diagno- sis of acute myocardial infarction (AMI) [15]. Their study utilizes the PTB-XL dataset, employing ECG images for analysis. Notably, the researchers introduce a low-pass filter in their data processing pipeline to enhance signal quality. The core of their approach lies in a custom Convolutional Neural Network (CNN). The model is rigorously evaluated using AUROC, precision, sensitivity, speci- ficity, and f-1 score, with a noteworthy 94.40% validation AUC. This high validation AUC underscores the effectiveness of their NN algorithm in achieving accurate and reliable AMI diagnosis.

In a recent study, Gustafsson S. et al. aim to predict myocardial infarction (MI) from electrocardiogram (ECG) signals utilizing deep learning models. The data employed for this study consists of clinically collected raw ECG signals [16]. Notably, the researchers applied high-pass filters during the data processing phase. The deep learning method chosen for this task is a custom Deep Neural Network (DNN). Evaluation matrices, including the C-statistic and Brier scores, were employed to assess the performance of their model. The obtained results are promising, with a C-statistic of 0.991 and a Brier score of 0.001, indicating high accuracy in predicting MI.

Jahmunah V. et al. present an innovative approach in their study by proposing a custom DenseNet and Convolutional Neu- ral Network (CNN) model for the classification of ECG signals [17]. Their data source is the Physikalisch-Technische Bunde- sanstalt (PTB) database, consisting of ECG signals. During the data processing phase, the researchers applied noise and baseline removal using the Daubechies 6 wavelet function. The chosen deep learning methods include DenseNet and CNN. The evalua- tion metrics employed for assessing the models' performance are accuracy, specificity, and sensitivity. Impressively, the proposed DenseNet achieved an accuracy of 98.9%, while CNN exhibited a commendable accuracy of 98.5

In their recent work, Hasbullah et al. aim to improve myocardial infarction (MI) detection utilizing Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) [18]. Their pri- mary goal is to enhance accuracy in identifying MI cases. The dataset chosen for this study is the PTB XL dataset, focusing on ECG images. Notably, the researchers employ a meticulous data preprocessing step, involving cleaning, before delving into fea- ture extraction using a combination of CNN and Long Short-Term Memory (LSTM) networks, denoted as CNN-LSTM. Addition- ally, a variant of this architecture, CNN-BILSTM, is explored. The evaluation metrics encompass accuracy, recall, precision, and f1-score. The results demonstrate substantial performance, with an accuracy of 89% for CNN-LSTM and 91% for CNN-BILSTM, highlighting the efficacy of their approach in MI detection.

Pham et al. contribute to the evolving landscape of cardiovas- cular diagnostics with a focus on arrhythmias and myocardial clas- sification [19]. Their study employs data from both the MIT-BH and PTB datasets, utilizing ECG signal data. The authors establish a comprehensive processing pipeline and leverage a Residual Con- volutional Neural Network (Residual-CNN) for their classification task. Evaluation metrics include accuracy, recall, and precision. The achieved results are highly promising, with an accuracy of 98.5% on the MIT-BH dataset and 98.28% on the PTB dataset, emphasizing the robustness of their model in effectively classify- ing arrhythmias and myocardial conditions.

While these studies showcase remarkable strides in advancing cardiovascular disease diagnostics, a notable gap emerges the ab- sence of dedicated research on AI assistance base applications to predict STEMI. This critical area remains unexplored, posing a significant opportunity for future investigations. Furthermore, the identified research gaps include the lack of studies assessing the performance of deep learning models in real-world clinical settings and the need for seamless integration with healthcare profession- als' workflows. Addressing these gaps becomes imperative for the holistic implementation of deep learning in practical health- care scenarios. To bridge these voids, a novel study is proposed. This study aims to develop a deep learning-based system tailored explicitly for the diagnosis of STEMI. The hypothesis underlying this endeavour posits that such a system, designed to seamlessly integrate with clinical workflows, will enhance the accuracy and efficiency of STEMI diagnosis. Ultimately, this intervention holds the potential to translate into improved patient outcomes, aligning

with the overarching goal of advancing cardiovascular healthcare through innovative technological solutions.

The research methodology in (Fig. 1) consists of 11 sequential steps, commencing with a comprehensive survey involving 237 participants to assess the urgency of an AI-based diagnosis system for pre-hospital emergencies. Following the survey, a meticulous analysis of the data was conducted, shaping the research trajectory based on key insights. Subsequently, a dataset was curated to align with research objectives, undergoing thorough pre-processing to optimize its utility for training purposes. The dataset was then partitioned into training and validation sets to facilitate systematic model training.

The model training phase utilized the prepared dataset to equip the model with the necessary knowledge for effective diagnos- tic capabilities. Evaluation of the model ensued, culminating in the generation of a comprehensive classification report. In the final steps, the trained model was strategically deployed to cre- ate a user-friendly application interface, bridging the gap between model development and real-world applicability for enhanced ac- cessibility.

A Details of the Survey

This section includes the survey questions, demographic in- formation of the participants, and the subsequent analysis of the survey data. Through analysis, we examined the survey responses, conducted statistical calculations, and drew conclusions.

A.1 Survey Questions

The survey encompassed a total of 10 questions (Table. I) , with participants providing ratings on a scale of 1 to 5. A rating of 1 represented strong disagreement, while a rating of 5 denoted strong agreement. These questions aimed to gather insights specif- ically related to the topic of AI in STEMI. In addition to the 10 survey questions, participants were also asked to provide demo- graphic information through five additional questions (Figure 2). These demographic-related questions covered important factors such as age, education level, work type, years of experience, and work region. Collecting this demographic data allowed for a more comprehensive analysis, considering potential variations or pat- terns based on different participant characteristics. The survey as a whole aimed to explore participants' perspectives, opinions, and experiences regarding the application of AI in STEMI. By combin- ing the survey responses and demographic information, valuable insights could be derived to inform decision-making, research, or advancements in this specific field.

A.2 Demographic Analysis

In Figure 2, the demographic information of the participants is presented, showcasing significant trends observed across different categories. The analysis of the participants' demographic data provided valuable insights into the characteristics of the survey respondents and their potential influence on the survey results.

Table I. Summary Of The Survey Data Analysis

ID	Questions	Rating
1	How important is it to have an artificial intelligent support system to quickly di- agnose and treat acute coronary syndrome (heart attack) (STEMI) in pre-hospital emergency medical services?	168 out of 237 responses rated 5
2	How important is the use of artificial intelligence for the speed and accuracy of chart reading and treatment of acute coronary syndrome (heart attack) (STEMI) in the pre-hospital setting?	168 out of 237 responses rated 5
3	How important is the impact of an artificial intelligent support system in reduc- ing the time from symptom onset to definitive treatment for pre-hospital acute coronary syndrome (heart attack) (STEMI) patients?	157 out of 237 responses rated 5
4	In your opinion, how important is it to enhance the efficiency and effectiveness of pre-hospital emergency medical services in the management of acute coronary syndrome (heart attack) (STEMI) cases to reduce on-site stay time?	168 out of 237 responses rated 5
5	How important is it to use advanced technologies such as artificial intelligence to quickly treat acute coronary syndrome (heart attack) (STEMI) by reminding you of the appropriate treatment at the pre-hospital stage?	165 out of 237 responses rated 5
6	To what extent do you think implementing an artificial intelligence support system could contribute to better patient outcomes and lower mortality rates for	147 out of 237 responses rated 5

	pre- hospital acute coronary syndrome (heart attack) (STEMI) cases?	
7	How important is it to provide healthcare workers in pre-hospital emergency services with an advanced support system that helps in the rapid diagnosis and treatment of acute coronary syndrome (heart attack) (STEMI)?	176 out of 237 responses rated 5
8	How important is it to allocate resources and invest in developing and implement- ing an AI support system for the management of acute coronary syndrome (heart attack) (STEMI)?	157 out of 237 responses rated 5
9	How valuable would it be to have a system that can provide real-time decision support and treatment recommendations for prehospital acute coronary syndrome (heart attack) (STEMI) cases?	170 out of 237 responses rated 5
10	How necessary is it to improve the quality and efficiency of comprehensive emergency medical services for patients with acute coronary syndrome (heart attack) (STEMI) by adopting an artificial intelligent support system?	172 out of 237 responses rated 5

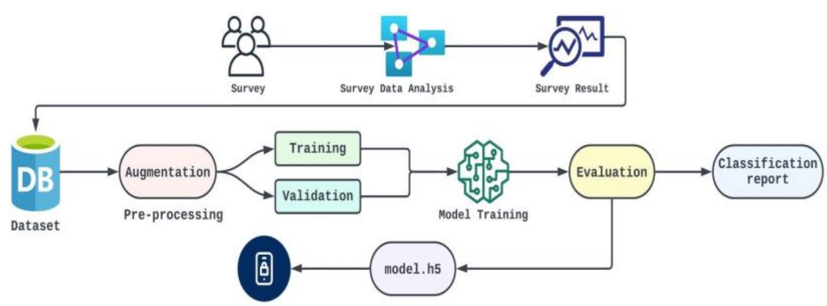

Fig. 1. Proposed AI-based diagnosis pipeline

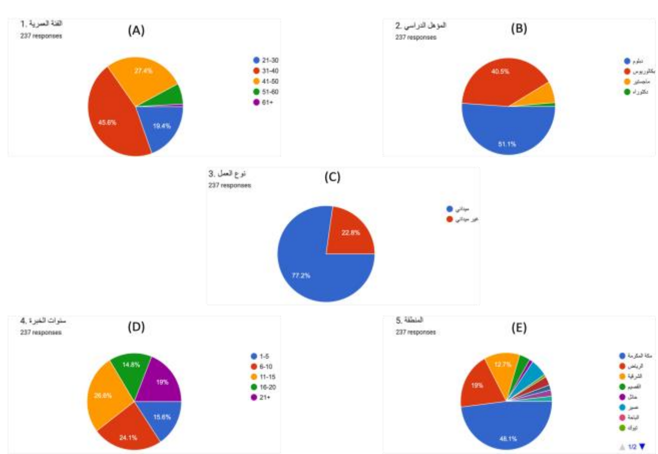

Fig. 2. Participants' demographic information

One noteworthy trend observed in the demographic informa- tion is the age distribution of the participants. The (Fig. 2 (A)) highlights five distinct age groups represented in the survey, indi- cating whether the respondents were predominantly from younger or older age brackets. The largest cohort falls within the 31-40 age range, followed by the 41-50 and 21-30 groups. Subsequently, the 51-60 age category is noted, with the smallest segment rep- resenting those aged 60 and above. This information can shed light on the generational perspectives and experiences regarding AI in STEMI, as different age groups may have varying levels of familiarity and comfort with technology.

Another important category depicted in (Fig. 2 (B)) is the education level of the participants. This information reveals the educational backgrounds of the respondents, such as whether they held undergraduate degrees, graduate degrees, or had other lev- els of educational attainment. the majority of participants hold Diploma degrees, positioning it as the largest group. Following closely are individuals with Bachelor's degrees. Notably smaller are the cohorts with Master's degrees, and a minority possess Ph.D. qualifications. This data can provide insights into the po- tential influence of education on participants' understanding and perceptions of AI in STEMI.

Furthermore, the (Fig. 2 (C)) presents the distribution of par- ticipants across different work types. It distinguishes between those in the field (refers to activities and operations that are con- ducted on-site or in response to emergencies, such as first aid at the scene of an accident) and those out of the field or non-operational (refers to activities that are conducted off-site, such as planning, administration, and training). The predominant work type among participants is identified as field workers, constituting the largest group. In contrast, the remaining participants are categorized as non-field workers. This differentiation provides valuable in- sights into the diverse perspectives and experiences related to AI in STEMI across different professional backgrounds.

Additionally, the demographic information in (Fig. 2 (D)) high- lights the distribution of participants based on their years of expe- rience in the field. This data categorizes respondents into groups representing different levels of professional experience, ranging from novice to experienced practitioners. Analysis of experience years reveals a significant group with 11-15 years of experience, marking it as the largest segment. The subsequent group holds 6-10 years of experience, followed by participants with 21+ years, 1-5 years, and 16-20 years of professional experience. This in- formation can provide insights into how the level of experience might influence participants' perceptions and attitudes towards AI in STEMI.

Lastly, (Fig. 2 (E)) illustrates the geographical breakdown of the participants, highlighting the regions or countries they come from. The participants' distribution across various work regions is organized in descending order, starting with the most represented groups: Makkah, Riyadh, Eastern, Al-Qassim, Hail, Assir, Al- Baha, Tabuk, Jazan, Najran, Aljouf, and Northern borders. This data can be valuable in identifying potential regional disparities in perspectives and experiences regarding AI in STEMI, taking into account the impact of cultural, regulatory, and healthcare system variations among different regions.

By examining the trends and patterns in the demographic in- formation presented in (Fig. 2), researchers and stakeholders can gain a deeper understanding of the diverse perspectives and poten- tial biases that may exist within the survey data. These insights

can inform further analysis and interpretation of the survey results, allowing for a more comprehensive understanding of the implica- tions of AI in STEMI across different demographic categories.

A.3 Survey Response Analysis

The survey results overwhelmingly demonstrate a consensus among participants (Table I), with 168 to 176 responses consis- tently rating each question with a score of 5, indicating strong agreement. The collective viewpoint emphasizes the critical im- portance of implementing an artificial intelligence (AI) support system in pre-hospital emergency medical services for the swift diagnosis and treatment of acute coronary syndrome (STEMI), commonly known as a heart attack. The participants express a strong belief in the potential of AI to enhance the speed and ac- curacy of chart reading, reduce the time from symptom onset to definitive treatment, and ultimately improve patient outcomes and lower mortality rates. The figures of the survey's responding graphs are available in the supplementary materials.

It also underscores the significance of AI in augmenting the efficiency and effectiveness of pre-hospital emergency medical services, with a specific focus on minimizing on-site stay time. Moreover, there is a unanimous call for allocating resources and investments to develop and implement AI support systems in man- aging acute coronary syndrome cases. The resounding agreement across all survey questions signals a clear mandate for the integra- tion of advanced technologies, such as real-time decision support and treatment recommendations, to revolutionize and elevate the quality of comprehensive emergency medical services for STEMI patients in the pre-hospital setting.

Lastly, the survey results strongly advocate for the emergence and development of an AI-based diagnosis system tailored for pre-hospital settings, highlighting the pressing need for advancements in this critical healthcare domain.

B Dataset Description

In this experiment, we employed the ECG Images dataset of Cardiac Patients [20]. The fundamental purpose behind curating this dataset is to facilitate the scientific community in their research endeavours focused on CVD specifically on STEMI. Further infor- mation about the dataset can be found in (Table. II).

B.1 Data Pre-processing

In the context of this experiment, the two available classes in the dataset were utilized for binary classification: STEMI and Nor- mal, containing 240 and 284 instances, respectively. The limited amount of data for prediction and the presence of data imbalance raised concerns, prompting the application of data augmentation as a remedial measure.

To address these challenges, various augmentation techniques were employed, encompassing rotation, width and height shift- ing, shearing, zooming, and horizontal flipping. These techniques were chosen to simulate diverse real-world scenarios and potential

variations that the model may encounter during training. For in- stance, rotation mimics alterations in the orientation of the images, shifts and shearing introduce variations in image positioning and shape, zooming adds variability in scale, and horizontal flipping simulates mirror images of the input.

The augmentation process involves iterating through the origi- nal images, applying the chosen techniques, and saving the newly generated images to the same directory. This systematic approach results in an expanded dataset, contributing to a more robust and diverse collection of images suitable for training a deep learning model. Specifically, two augmented images are generated for each original image, effectively tripling the dataset size for the ”Normal and STEMI class” class (Table. III).

C Data Splitting

The augmented data classes, designated as the new dataset, are meticulously divided into distinct training and validation sets (Table. IV). Comprising 80% of the data, the training set is thoughtfully curated through a randomized process to facilitate effective model training. Concurrently, the validation set, consti- tuting 20% of the data, remains segregated throughout the training phase, functioning as an autonomous dataset for intricate perfor- mance evaluation. This sophisticated data-splitting methodology proves crucial for identifying and mitigating potential overfitting, substantiating the model's robustness.

The deliberate separation of training and validation sets instil confidence in the model's broader generalization capabilities, a critical aspect for its application to diverse and novel instances. This approach reflects a balanced and strategic framework, intri- cately designed to optimize the model's learning process while rigorously evaluating its adaptability and efficacy in addressing real-world scenarios.

D Model Training

This training methodology, characterized by careful data segre- gation, strategic layer freezing, and model evaluation, establishes a robust framework for training a deep learning model on selected ECG image data. In the model training phase, a data generator efficiently manages augmented image data, streaming it from a designated directory to expose the model to diverse examples. A separate validation data generator is concurrently established to as- sess the model's performance on an independent subset, ensuring an unbiased evaluation of its generalization capabilities. Lever- aging the pre-trained ResNet50 model as a foundation, initially trained on ImageNet, its layers are frozen to preserve knowledge from the pre-training phase (Fig. 3). Atop ResNet50, a custom model is crafted, featuring a flattening layer followed by dense layers. The final layer employs a sigmoid activation function for binary classification.

The model is compiled with a binary cross-entropy loss func- tion and the Adam optimizer. Over ten epochs, the training pro- cess unfolds, allowing the model to learn discerning patterns in

Table II. Details of the dataset

Total patient	Data type	Data class	Image count	Image resolution
12	JPG	STEMI	240	2213 × 1572
12	JPG	Normal	285	2213 × 1572

Table III. Number of instances in each class in the final dataset

Number of Instances in Both Class Before Augmentation	STEMI	240	Normal	285
Number of Instances in Both Class After Augmentation	STEMI	469	Normal	549
Number of Instances in Both Class in the Final Dataset	STEMI	709	Normal	834

the augmented ECG image dataset. Accuracy and loss metrics are vigilantly monitored throughout this iterative training. Strategi- cally freezing the pre-trained layers empowers the model to capture generic features from ImageNet, while subsequent layers specialize in task-specific information for image classification. This layered approach ensures efficient training on a relatively small dataset, blending pre-learned features with task-specific adaptations.

We tested and compared ResNet50, EfficientNetB0, and DenseNet121 to determine the best algorithm for classifying aug- mented ECG images. ResNet50's deep architecture with skip connections addresses the vanishing gradient problem while also capturing intricate features, making it ideal for large datasets. Ef-

instances correctly predicted as positive, while True Negatives (TN) represents the number of instances correctly predicted as negative. On the other hand, False Positives (FP) indicate the number of instances predicted as positive when they are actually negative, and False Negatives (FN) represent instances predicted as negative when they are actually positive.

Accuracy 1, as a foundational metric, measures the proportion of correctly classified instances out of the total predictions. It provides a fundamental assessment of the model's performance and is calculated by dividing the number of correct predictions by the total predictions.

ficientNetB0's balanced scaling of network width, depth, and res- olution enables state-of-the-art performance with fewer parame- ters, providing an excellent balance of accuracy and efficiency for

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

augmented ECG classification. DenseNet121's dense connectiv- ity pattern encourages feature reuse and gradient flow, allowing deeper networks without vanishing gradients. After testing the three models and comparing their results, ResNet50 was chosen due to its 50-layer depth, adeptly capturing intricate signal fea-

Precision 2 evaluates the model's accuracy in positive predic- tions. It quantifies the model's ability to make precise affirmative classifications and is calculated by dividing the number of true positives by the sum of true positives and false positives.

tures, and addressing training nuances with residual connections. Pre-training on ImageNet supports effective transfer learning, im- proving performance with limited ECG data. Compared to basic

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

CNNs, ResNet50 excels in image classification, crucial for dis- cerning subtle ECG details, while its balanced complexity and efficiency make it suitable for moderate datasets without excessive computational demands. ResNet50's preference over deeper mod- els like DenseNet is grounded in practical considerations, lever- aging its architecture, especially residual connections, to expedite training and address nuanced ECG patterns efficiently.

E Evaluation Metrics

During the comprehensive evaluation of our machine learning model, four crucial metrics, namely Accuracy, Precision, Recall, and F1-Score, play a vital role in assessing its overall performance. Each metric provides unique insights into the model's ability to

Recall 3, also known as sensitivity or the true positive rate, as- sesses the model's effectiveness in capturing all positive instances. It is calculated by dividing the number of true positives by the sum of true positives and false negatives.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

The F1-Score 4, which combines precision and recall into a single metric, offers a balanced evaluation of the model's overall performance. It is calculated using the harmonic mean of precision and recall.
accurately classify instances and handle errors.

To begin with, True Positives (TP) represents the number of

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (4)$$

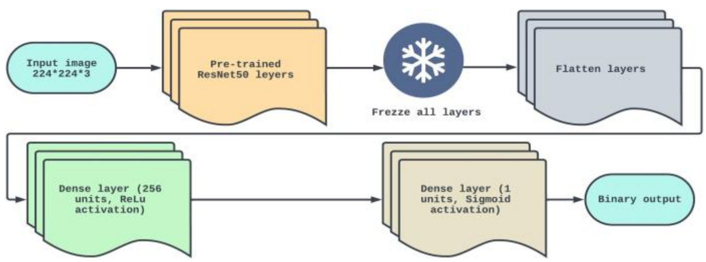

Fig. 3. DeepSTEMI model architecture based on the pre-trained ResNet50 model

Table IV. Data count in different data splits

Data Split	Data Count
STEMI (Training)	568
STEMI (Validation)	141
Normal (Training)	668
Normal (Validation)	166

In addition to these essential evaluation metrics, the training and validation plots provide further insights into the model's learn- ing dynamics over epochs. Visualizations of accuracy and loss trends during the training and validation phases offer valuable in- form

Fig. 4. DeepSTEMI web tool for STEMI prediction

F Model Deployment and Web-tool Creation

To create an interactive application, we used a pre-trained.h5 model and the Flask framework. With the use of this application, users can quickly upload medical photos from datasets, allow- ing our AI assistant to differentiate between normal instances and STEMI (Fig. 4) and deliver prompt diagnosis.

The application extends valuable initial treatment suggestions. Detailed information, including prediction accuracy, prediction time, and the date and time of the analysis, is provided to users. The uploaded medical image is dynamically showcased on the screen, enhancing the user experience and facilitating well- informed decision-making in cardiac health assessment.

III. RESULT ANALYSIS AND DISCUSSION

The evaluation results present a detailed breakdown of ResNet50's, DenseNet's, and EfficientNet's performance across two distinct classes: STEMI and Normal instances. These met- rics: Precision, Recall, F-1 Score, and Accuracy offer insights into how well the model accurately identifies instances from each class (Table. V VI VII).

Table V. Result analysis of the classification task of EfficientNet

Data Class	Precision	Recall	F-1 score
0 (STEMI)	1.00	0.79	0.88
1 (Normal)	0.65	1.00	0.79
Accuracy: 0.85			

In Table V the class corresponding to STEMI, the precision is noted at 1.00. This implies that when the model predicts an instance as STEMI, it is correct 100% of the time. The recall for STEMI is 0.79, indicating the model successfully captures 79% of all actual STEMI instances. The F-1 Score, a harmonic mean of precision and recall, is calculated at 0.88. This metric considers both precision and recall, providing a holistic view of the model's performance.

On the other, in the class corresponding to Normal instances, the precision is 0.65, signifying that when the model predicts an instance as Normal, it is accurate 65% of the time. The recall for Normal instances is 1.00, indicating that the model successfully identifies 100% of all actual Normal instances. The F-1 Score for this class is 0.79, representing the assessment of precision and recall.

Table VI. Result analysis of the classification task of EfficientNet

Data Class	Precision	Recall	F-1 score
0 (STEMI)	0.94	0.96	0.95
1 (Normal)	0.89	0.86	0.87
Accuracy: 0.93			

In Table VI the class corresponding to STEMI, the precision is noted at 0.94. This implies that when the model predicts an instance as STEMI, it is correct 94% of the time. The recall for STEMI is 0.96, indicating the model successfully captures 96% of all actual STEMI instances. The F-1 Score, a harmonic mean of precision and recall, is calculated at 0.95. This metric considers both precision and recall, providing a holistic view of the model's performance.

On the other, in the class corresponding to Normal instances, the precision is 0.89, signifying that when the model predicts an instance as Normal, it is accurate 89% of the time. The recall for Normal instances is 0.86, indicating that the model successfully identifies 86% of all actual Normal instances. The F-1 Score for this class is 0.87, representing the assessment of precision and recall.

Table VII. Result analysis of the classificationtask of EfficientNet

Data Class	Precision	Recall	F-1 score
0 (STEMI)	0.96	0.97	0.97
1 (Normal)	0.95	0.96	0.96
Accuracy: 0..97			

Finaly in Table VII the class corresponding to STEMI, the precision is noted at 0.96. This implies that when the model predicts an instance as STEMI, it is correct 96% of the time. The recall for STEMI is 0.97, indicating the model successfully captures 97% of all actual STEMI instances. The F-1 Score, a harmonic mean of precision and recall, is calculated at 0.97. This balanced metric considers both precision and recall, providing a holistic view of the model's performance.

On the other, in the class corresponding to Normal instances, the precision is 0.95, signifying that when the model predicts an instance as Normal, it is accurate 95% of the time. The recall for Normal instances is 0.96, indicating that the model successfully identifies 96% of all actual Normal instances. The F-1 Score for this class is 0.96, representing a harmonized assessment of precision and recall.

ResNet50 outperforms EfficientNet and DenseNet121, achiev- ing an overall accuracy of 0.97 for Class 0 and 1, indicating that 97% of STEMI and normal instances are correctly predicted. These results indicate that the model exhibits strong performance in distinguishing between Myocardial Infarction and Normal in- stances. The high precision and recall values, along with balanced F-1 scores, reflect the model's accuracy and effectiveness in clas- sifying instances from both classes.

Performance evaluation of the DeepSTEMI model, as depicted in (Fig.5), underscores its highly promising capabilities. However, the training and validation accuracy and loss plots provide crucial

insights into the model's learning dynamics.

The reported training and validation loss, standing at 0.13019, signifies the average dissimilarity between predicted and true labels throughout the training phase. The accompanying loss plot exhibits a smooth curve, affirming the model's proficiency in minimizing errors and optimizing its predictive accuracy. This characteristic suggests that the model has successfully learned to capture intricate patterns in the training data.

While the accuracy plot may exhibit some discrepancies at- tributable to the diverse augmentation images and the substantial volume of data, the overall test accuracy remains consistent with the training accuracy, reaching an impressive 97.17%. This align- ment serves as a strong indicator of the model's robust generaliza- tion to new, unseen data. The model's ability to maintain similar accuracy levels on both training and test datasets underscores its reliability and efficacy.

In the accompanying visual representation of the training and test accuracy, the convergence of the curves indicates that the model effectively learns from the training data and exhibits robust generalization to the test data. The consistent and high accuracy values, coupled with the relatively low loss, collectively signify a well-performing model.

Lastly, this experiment sought a

comprehensive understanding of the model's performance by generating a Receiver Operating Characteristic (ROC) curve in (Fig.6) which is a powerful visu- alization graph, that enables a nuanced assessment of a model's ability to discriminate between classes across various decision thresholds. In this case, the ROC curve was derived from the predictions of the ResNet50 model.

Notably, the AUC score, a quantitative measure derived from the ROC curve, serves as a key indicator of the model's discrimina- tive prowess. The ResNet50 model, upon evaluation, exhibited an impressive AUC score of 0.98. This high AUC score substantiates the model's exceptional performance in distinguishing between classes, reinforcing its efficacy in classifying instances within the context of our study.

To sum up, the ResNet50 model demonstrated strong and con- sistent performance across a spectrum of evaluation metrics. Its ability to accurately and reliably classify cardiac instances under- scores its potential utility in tasks associated with cardiovascular image classification. These results not only validate the model's effectiveness but also emphasize its prospective contributions to the ongoing advancements in the field of medical image analysis.

IV. CONCLUSION AND FUTURE DIRECTION

In conclusion, this research endeavours to harness technologi- cal advancements with the primary aim of substantially mitigating on-site durations for medical teams, particularly in the context of cardiac emergencies. The imperative nature of this research is underscored by a meticulous statistical analysis conducted in the Makkah region, revealing prolonged on-site durations that harbor potential adverse implications for patient outcomes.

The future trajectory of this study emphasizes the pragmatic

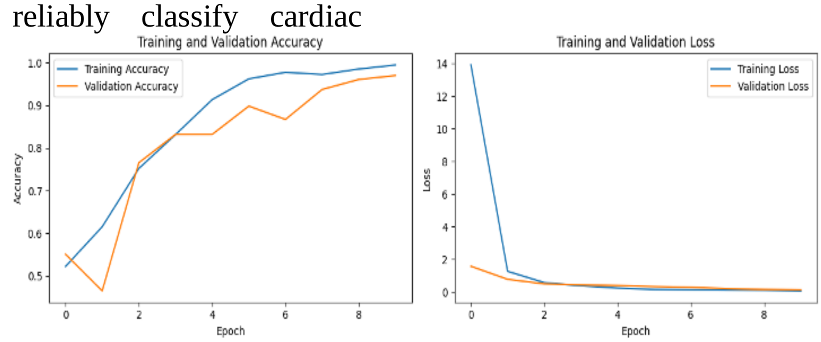

Fig. 5. Training and validation accuracy and loss plots of DeepSTEMI

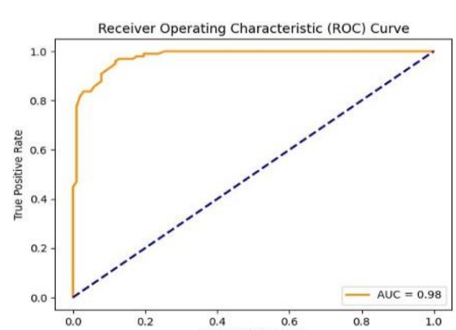

Fig. 6. AUC/ROC of DeepSTEMI model

implementation and validation of the AI-based diagnosis system through collaboration with healthcare institutions. Continuous re- finement of the model will be essential, ensuring its adaptability to the evolving landscape of healthcare scenarios. Additionally, the expansion of the system to cover a broader spectrum of cardiac conditions is envisaged, promising enhanced diagnostic capabili- ties and applicability in diverse clinical scenarios. Integrating real-time data feeds and mechanisms for continuous learning stands out as a promising avenue for elevating the system's responsiveness and diagnostic precision.

Acknowledging the current focus on binary classification of STEMI and normal cases as a limitation, future developments aim to transform the system into a comprehensive multi-cardiovascular disease (CVD) diagnosis tool. This evolution will enhance the sys- tem's versatility, providing healthcare practitioners with a holistic diagnostic solution. As part of future work, training the model with a large-scale dataset comprising real-life data is envisioned to augment robustness and generalization capabilities across diverse clinical scenarios.

In essence, this research lays a robust academic foundation for the seamless integration of AI into pre-hospital emergency medical services, promising far-reaching implications for the expeditious and effective management of cardiac care. Aligned with the Saudi Red Crescent Authority's mission to reduce the impact of heart attacks and in line with the healthcare objectives of Saudi Vi-
sion 2030, the proposed DeepSTEMI model aims to substantially enhance the quality of life for patients by delivering timely and effective interventions.

DECLARATIONS

- Authors' contributions: S.A. and Ab.A. conceptualized the study and designed and developed the overall framework of the DeepSTEMI system. R.E. and L.A. were responsible for gathering and analyzing relevant literature and research in the field. S.A. provided guidance and expertise in the field of ar- tificial intelligence and machine learning. Ab.A. collaborated with the team to ensure the clinical relevance and accuracy of the DeepSTEMI system. Ab.A., F.A. and Ah.A. assisted in the critical review of the manuscript. All authors, includ- ing S.A., Ab.A., R.E., L.A., F.A., and Ah.A., contributed to the design and development of the user interface. Addi- tionally, all authors, including S.A., Ab.A., R.E., L.A., F.A., and Ah.A., made significant contributions to the writing and revision of the manuscript. Finally, all authors reviewed the manuscript to ensure its accuracy and quality.
- Availability: All the data and code related to the Deep- STEMI project are available at the following GitHub repos- itory:

https://github.com/SomayahAlbaradei/DeepSTEMI.

The repository contains the necessary files, including the ECG application, templates, the main machine learning model, and a README.md file providing additional information. By ac- cessing the provided URL, users can view and download the available resources for further exploration, analysis, and uti- lization.

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نظام الدعم الذكي اصطناعيا للتشخيص السريع وعلاج ارتفاع احتشاء عضلة القلب في مرحلة خدمات الطوارئ الطبية ما قبل المستشفى في مكة المكرمة

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مستخلص. يتناول هذا البحث الضرورة الحاسمة لتحسين رعاية القلب في خدمات الطوارئ قبل المستشفى من خلال دمج نظام التشخيص القائم مع الذكاء الاصطناعي. سلطت دراسة استقصائية شملت 237 مشاركاً في المملكة العربية السعودية الضوء على الحاجة الأساسية لتقليل فترات البقاء في الموقع أثناء حالات الطوارئ القلبية، مع اتفاق بالأجماع بين المشاركين بشأن الدور المحوري للذكاء الاصطناعي في تسريع الاستجابات، كما يوفر التحليل الديموغرافي رؤى حول اتجاهات المشاركين، مما يساهم في فهم الخلفية الشاملة. تقترح الدراسة منهجية تشمل العناصر الأساسية، بما في ذلك زيادة البيانات، والتدريب على نموذج ResNet50، وتطوير مساعد الذكاء الاصطناعي سهل الاستخدام المسمى DeepSTEMI. تم تصميم مساعد الذكاء الاصطناعي هذا التنبؤ على وجه التحديد باحتشاء عضلة القلب (STEMI) من صور معينة والاستجابة للعلاج الأولي. يظهر النموذج باستمرار دقة عالية وتؤكد المنطقة التي تم التحقق من صحتها تحت المنحنى (AUC) والتي تبلغ 98.0 على براعة النموذج التمييزية في التمييز بين احتشاء عضلة القلب (STEMI) والحالات العادية. ومن أجل التعامل مع مجموعة واسعة من مشاكل القلب، توصي الدراسة بالتطوير المستمر للنموذج، والتعاون مع هيئة الهلال الأحمر السعودي. تؤكد الدراسة أيضاً على مدى أهمية دمج التعلم المستمر وتدفقات البيانات في الوقت الفعلي لتحسين دقة التشخيص.

الكلمات المفتاحية. احتشاء عضلة القلب، هيئة الهلال الأحمر السعودي، خدمات الطوارئ قبل المستشفى، التعلم العميق.