"Artificial Intelligence (AI) Based Clinical Decision Support System (CDSS) for Acute Emergency Care (AEC) of Stemi Patients Based on Standardized Management Protocol at Parul Sevasthram Hospital, Vadodara, Gujarat."

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ABSTRACT

Background

Acute emergency care (AEC) for ST-segment elevation myocardial infarction (STEMI) is a critical area in cardiology, where timely and accurate decisions can significantly impact patient outcomes. STEMI, a severe form of heart attack, occurs due to the complete blockage of a coronary artery, leading to substantial myocardial damage if not treated promptly. Traditional management protocols for STEMI, such as the guidelines provided by the American College of Cardiology (ACC) and the American Heart Association (AHA), emphasize rapid diagnosis, timely reperfusion therapy, and continuous monitoring. However, the complexity and urgency of these cases present challenges that can benefit from advanced technological interventions, particularly AI-based Clinical Decision Support Systems (CDSS).

Current Challenges in STEMI Management

The management of STEMI involves several critical steps, including early recognition, risk stratification, selection of appropriate therapeutic interventions, and post-treatment monitoring. These steps require the integration of vast amounts of clinical data, rapid decision-making, and coordination among multidisciplinary teams. Despite established protocols, variability in clinical practice and delays in treatment initiation often occur, leading to suboptimal patient outcomes. Factors contributing to these challenges include: Data Overload, Time Sensitivity, and Clinical Variability

Development and Integration of AI-Based CDSS

The development of an AI-based CDSS for STEMI involves several stages, including data collection, algorithm training, system validation, and integration into clinical practice. This process requires collaboration between cardiologists, data scientists, and IT specialists. Key steps include:

1. **Data Collection and Preprocessing**: Aggregating and standardizing data from various sources, such as EHRs, imaging systems, and wearable devices, ensuring data quality and consistency.
2. **Algorithm Development**, Training machine learning models on large datasets to recognize patterns and make predictions. This involves selecting appropriate features, tuning model parameters, and evaluating performance using metrics like accuracy, sensitivity, and specificity.
3. **Clinical Validation**: Testing the AI system in real-world settings to assess its reliability, safety, and effectiveness. This involves pilot studies, randomized controlled trials, and feedback from clinicians.

INTRODUCTION

What is ST-elevation Myocardial Infarction (STEMI)?

ST-elevation Myocardial Infarction (STEMI) is a critical medical condition characterized by the occlusion of one or more coronary arteries, leading to a lack of blood supply to a specific area of the heart muscle, known as the myocardium. This ischemic event results in irreversible damage to the affected myocardial tissue and can have severe consequences if not promptly diagnosed and treated. STEMI is considered a medical emergency and requires immediate intervention to prevent further myocardial damage and potential complications such as arrhythmias, heart failure, or even death.

Epidemiology

STEMI accounts for a significant proportion of acute coronary syndromes (ACS) and remains one of the leading causes of morbidity and mortality worldwide. The incidence of STEMI varies among different populations and is influenced by factors such as age, sex, ethnicity, lifestyle, and socioeconomic status. While advancements in medical therapy and interventions have contributed to a decline in mortality rates associated with STEMI in recent years, it still poses a considerable public health burden globally.

Pathophysiology

The pathophysiology of STEMI involves the formation of a thrombus (blood clot) within a coronary artery, usually as a result of the rupture or erosion of an atherosclerotic plaque. This thrombotic occlusion leads to a sudden interruption of blood flow to the myocardium distal to the blockage, causing ischemia and subsequent necrosis of the affected myocardial tissue. The degree and duration of coronary artery occlusion determine the extent of myocardial damage and the severity of clinical presentation.

Clinical Presentation

The clinical presentation of STEMI can vary depending on several factors, including the location and size of the infarcted area, the presence of collateral circulation, and individual patient characteristics. However, typical symptoms of STEMI often include severe chest pain or discomfort that may radiate to the arms, neck, jaw, back, or abdomen. Other associated symptoms may include shortness of breath, nausea, vomiting, diaphoresis (excessive sweating), and lightheadedness. It is essential to recognize that some patients, particularly the elderly, diabetics, or those with atypical presentations, may not experience chest pain or may present with subtle symptoms, making diagnosis challenging.

Diagnostic Evaluation

The diagnosis of STEMI is primarily based on clinical history, physical examination, and electrocardiographic (ECG) findings. A 12-lead ECG is the cornerstone of initial evaluation in patients suspected of having STEMI. The characteristic ECG changes indicative of myocardial infarction include ST-segment elevation (typically greater than 1 mm in two contiguous leads) and the development of pathological Q waves in the affected leads. Additional diagnostic modalities such as cardiac biomarkers (e.g., troponin) and imaging studies (e.g., echocardiography, coronary angiography) may be utilized to confirm the diagnosis, assess myocardial damage, and identify underlying coronary artery disease.

Management

The management of STEMI involves a multidisciplinary approach aimed at restoring coronary blood flow, salvaging ischemic myocardium, and preventing further complications. The primary goal of treatment is to achieve reperfusion of the occluded coronary artery as quickly as possible, preferably within the "golden hour" of symptom onset, to minimize myocardial injury and improve outcomes. Reperfusion strategies may include pharmacological reperfusion with fibrinolytic therapy or mechanical reperfusion via percutaneous coronary intervention (PCI) with stent placement. The choice of reperfusion strategy depends on various factors, including the time elapsed since symptom onset, patient's clinical stability, availability of interventional facilities, and individualized risk assessment.

Why AI?

Incorporating Artificial Intelligence (AI) into Clinical Decision Making for Acute Cardiac Emergencies (STEMI)

The field of medicine, particularly in the realm of acute cardiac emergencies, is witnessing a paradigm shift with the integration of Artificial Intelligence (AI) into clinical decision-making processes. Acute cardiac emergencies, such as ST-elevation Myocardial Infarction (STEMI), demand timely and accurate interventions to optimize patient outcomes. AI, with its ability to process vast amounts of data, identify patterns, and generate predictive models, holds immense potential in enhancing the diagnosis, risk stratification, and management of acute cardiac events. This essay explores the rationale and benefits of incorporating AI in clinical decision-making for acute cardiac emergencies.

Rationale for AI Integration

The integration of AI in acute cardiac care is driven by several factors:

1. Data Complexity: Acute cardiac emergencies involve a myriad of clinical, biochemical, electrocardiographic, and imaging data. AI algorithms can efficiently process and analyze these complex datasets to extract meaningful insights, aiding in accurate diagnosis and risk assessment.
2. Time Sensitivity: Time is of the essence in acute cardiac emergencies, where delays in diagnosis and treatment can significantly impact patient outcomes. AI-powered decision support systems can expedite the diagnostic process by rapidly interpreting diagnostic tests, identifying high-risk patients, and facilitating prompt interventions.
3. Personalized Medicine: Each patient presents with unique clinical characteristics, comorbidities, and risk factors, necessitating personalized treatment strategies. AI algorithms can leverage patient-specific data to tailor treatment plans, predict individual prognosis, and optimize therapeutic interventions based on personalized risk profiles.
4. Clinical Expertise Augmentation: AI serves as a complementary tool to augment clinical expertise by providing evidence-based recommendations, aiding in differential diagnosis, and assisting in complex decision-making scenarios. Clinicians can leverage AI-generated insights to make more informed decisions, thereby enhancing diagnostic accuracy and treatment efficacy.

Benefits of AI Integration

The integration of AI into clinical decision-making for acute cardiac emergencies offers several potential benefits:

1. Improved Diagnostic Accuracy: AI algorithms can analyze electrocardiographic (ECG) tracings, cardiac biomarker levels, and imaging studies with high sensitivity and specificity, facilitating early and accurate diagnosis of acute cardiac conditions such as STEMI.
2. AI-driven prediction models facilitate improved risk stratification, aiding in the early identification of patients susceptible to adverse cardiac events. This early recognition enables proactive intervention and intensified monitoring of high-risk individuals, ultimately averting complications and enhancing overall outcomes.
3. Streamlined Workflow: AI-powered decision support systems can automate routine tasks, prioritize critical alerts, and provide real-time guidance to healthcare providers, streamlining workflow efficiency and reducing cognitive workload in high-pressure clinical settings.
4. Predictive Analytics: AI algorithms can analyze longitudinal patient data to predict future cardiac events, such as recurrent myocardial infarctions or sudden cardiac death, allowing clinicians to implement preventive measures and optimize long-term management strategies.
5. Continuous Learning and Improvement: AI systems can continuously learn from new data inputs and clinical outcomes, refining their algorithms over time to adapt to evolving patient characteristics, disease patterns, and treatment modalities, thereby enhancing their predictive accuracy and clinical utility.

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Challenges and Considerations

Despite the promising potential of AI in acute cardiac care, several challenges and considerations must be addressed:

1. Data Quality and Standardization: AI algorithms depend on high-quality, standardized data inputs to function optimally. Variability in data collection methods, documentation practices, and interoperability between healthcare systems can challenge the accuracy and reliability of AI-generated predictions.
2. Interpretability and Transparency: The opaque nature of some AI algorithms raises concerns about their interpretability and transparency. Clinicians may be reluctant to trust AI-generated recommendations without understanding the reasoning behind the predictions.
3. Regulatory and Ethical Considerations: Implementing AI in clinical decision-making requires adherence to regulatory guidelines, data privacy regulations, and ethical principles governing patient autonomy, informed consent, and algorithmic transparency.
4. Integration into Clinical Workflow: Successful incorporation of AI into clinical practice requires seamless interoperability with existing electronic health record (EHR) systems, user-friendly interfaces, and clinician acceptance. Resistance to change, lack of training, and workflow disruptions may impede the adoption of AI technologies in acute cardiac care settings.

Integrating Artificial Intelligence (AI) into clinical decision-making processes holds great promise for optimizing the management of acute cardiac emergencies. AI-driven decision support systems can improve diagnostic accuracy, risk stratification, and treatment optimization, leading to better patient outcomes and healthcare delivery. However, addressing challenges related to data quality, interpretability, regulatory compliance, and workflow integration is crucial to realizing the full potential of AI in acute cardiac care. Collaborative efforts among clinicians, data scientists, regulatory agencies, and healthcare stakeholders are necessary to harness the transformative power of AI and advance the field of acute cardiac medicine.

Human-AI Cooperation in CDSS

Human-AI Cooperation: Enhancing Collaboration for Optimal Outcomes

Human-AI cooperation, also known as symbiotic or collaborative intelligence, refers to the synergistic interaction between humans and Artificial Intelligence (AI) systems to achieve complementary strengths and capabilities for solving complex problems and enhancing decision-making processes. In various domains, including healthcare, finance, education, and industry, the integration of AI technologies alongside human expertise has the potential to amplify productivity, innovation, and efficiency. This essay explores the principles, benefits, challenges, and future prospects of human-AI cooperation.

Principles of Human-AI Cooperation

Human-AI cooperation is guided by several key principles:

1. Complementarity: Humans and AI systems possess distinct strengths and capabilities. Human intelligence excels in creativity, emotional intelligence, and contextual understanding, while AI excels in data processing, pattern recognition, and computational efficiency. By leveraging each other's strengths, humans and AI can achieve synergistic outcomes that exceed the capabilities of either alone.
2. Mutual learning between humans and AI entails a collaborative process where both entities engage in reciprocal learning and adaptation. Humans provide feedback, guidance, and contextual knowledge to AI systems, enabling them to learn from human expertise and improve their performance gradually. Conversely, AI systems contribute to human decision-making by providing insights, recommendations, and predictive analytics derived from data-driven analysis and pattern recognition.
3. Shared Autonomy: Human-AI cooperation emphasizes shared autonomy, where humans and AI collaborate in decision-making processes, with each contributing according to their respective

strengths and expertise. Rather than replacing human agency, AI augments human intelligence and facilitates more informed, data-driven decision-making.

4. Transparency and Trust: Trust is paramount in human-AI cooperation. Transparent AI systems that provide explanations, justifications, and insights into their decision-making processes foster trust and acceptance among human users. Ensuring transparency and accountability in AI algorithms enhances user confidence and promotes effective collaboration.

Benefits of Human-AI Cooperation

Human-AI cooperation offers several potential benefits across various domains:

1. Enhanced Productivity: By automating routine tasks, augmenting human capabilities, and streamlining decision-making processes, human-AI collaboration can boost productivity and efficiency in complex work environments. AI systems can handle repetitive, data-intensive tasks, allowing humans to focus on higher-order cognitive activities that require creativity, intuition, and strategic thinking.
2. Improved Decision-Making: AI technologies can analyze vast amounts of data, identify patterns, and generate insights to support human decision-making. By synthesizing diverse sources of information, mitigating cognitive biases, and providing evidence-based recommendations, AI systems empower humans to make more informed, data-driven decisions with greater accuracy and confidence.
3. Innovation and Creativity: Human-AI collaboration stimulates innovation and creativity by facilitating the exploration of novel solutions, alternative perspectives, and interdisciplinary approaches to complex problems. AI algorithms can generate hypotheses, simulate scenarios, and optimize designs, while humans contribute domain expertise, intuition, and critical thinking to drive innovation forward.
4. Personalized Services: AI-driven personalization enables tailored experiences and services that cater to individual preferences, needs, and behavior patterns. In healthcare, finance, education, and customer service, AI algorithms can analyze user data, predict preferences, and customize recommendations, delivering personalized solutions that enhance user satisfaction and engagement.

Challenges and Considerations

Despite its potential benefits, human-AI cooperation faces several challenges and considerations:

1. Ethical and Social Implications: Human-AI collaboration raises ethical concerns related to privacy, bias, fairness, accountability, and autonomy. Ensuring ethical AI design, responsible data stewardship, and equitable access to AI technologies is essential to mitigate potential risks and uphold ethical principles.
2. Human-AI Trust and Acceptance: Building trust and acceptance in AI systems is crucial for successful collaboration. Human users may be skeptical of AI's capabilities, distrustful of opaque algorithms, or apprehensive about job displacement. Enhancing transparency, explain ability, and user engagement can foster trust and acceptance in human-AI cooperation.
3. Skills and Education: Human-AI collaboration requires interdisciplinary skills, digital literacy, and adaptive learning capabilities. Closing the skills gap and providing continuous education and training in AI literacy, data analytics, and human-computer interaction is essential to empower individuals to leverage AI technologies effectively and responsibly.
4. Regulatory and Legal Frameworks: Human-AI cooperation raises legal and regulatory challenges related to liability, accountability, intellectual property, and data protection. Establishing clear legal frameworks, standards, and guidelines for AI governance, transparency, and accountability is necessary to address regulatory concerns and ensure compliance with ethical and legal principles.

Future Prospects

The future of human-AI cooperation holds immense potential for innovation, progress, and societal impact. Emerging trends such as explainable AI, human-centered design, collaborative robotics, and decentralized AI systems are reshaping the landscape of human-AI interaction. As AI technologies continue to advance, human-AI collaboration will become increasingly integral to addressing complex challenges, driving economic growth, and enhancing human well-being across diverse domains.

Human-AI cooperation represents a transformative approach to problem-solving, decision-making, and innovation in the digital age. By harnessing the complementary strengths of humans and AI systems, we can unlock new opportunities for productivity, creativity, and societal advancement. However, addressing ethical, social, and technical challenges is essential to realizing the full potential of human-AI collaboration and ensuring that AI technologies serve the collective interests of humanity. Through responsible AI development, transparent governance, and inclusive collaboration, we can harness the power of human-AI cooperation to create a more prosperous, equitable, and sustainable future for all.

Using AI to Support Decision in STEMI

Utilizing Artificial Intelligence to Enhance Decision Support in ST-Elevation Myocardial Infarction (STEMI): A Comprehensive Flow Analysis

ST-elevation myocardial infarction (STEMI) represents a critical medical emergency requiring swift and accurate clinical decision-making to optimize patient outcomes. In recent years, the integration of Artificial Intelligence (AI) technologies has shown promise in supporting healthcare providers in the diagnosis, risk stratification, and management of acute cardiac conditions. This comprehensive flow analysis explores the role of AI in facilitating decision support throughout the continuum of care for STEMI patients, from initial presentation to long-term management.

1. Pre-Hospital Phase

a. Identification and Triage:

- AI algorithms integrated into emergency medical service (EMS) systems can analyze pre-hospital data, including dispatch information, patient demographics, and vital signs, to identify high-risk individuals with suspected STEMI.

- Machine learning models trained on historical data can prioritize ambulance dispatch, optimize resource allocation, and expedite transportation to the nearest PCI-capable hospital.

b. ECG Interpretation:

- **AI-powered mobile applications and wearable devices equipped with real-time ECG analysis capabilities can assist first responders in interpreting ECG tracings and identifying ST-segment elevation indicative of STEMI**.

- Cloud-based AI platforms can provide immediate feedback on ECG interpretations, enabling timely communication with receiving hospitals and activation of the cardiac catheterization lab.

2. Emergency Department Evaluation

a. Rapid Triage and Assessment:

- AI-driven triage systems can prioritize STEMI patients upon arrival, facilitating prompt evaluation by emergency department (ED) staff.

- Natural language processing (NLP) algorithms can extract pertinent information from electronic health records (EHRs) and triage notes to identify high-risk features and expedite clinical assessment.

b. Decision Support:

- AI algorithms integrated into EHR systems can analyze clinical data, including patient history, vital signs, laboratory results, and imaging studies, to calculate risk scores (e.g., TIMI, GRACE) and predict adverse outcomes.

- Machine learning models can generate differential diagnoses, recommend appropriate diagnostic tests (e.g., cardiac biomarkers, echocardiography), and stratify patients based on their likelihood of STEMI and need for urgent reperfusion therapy.

3. Diagnostic Workup

a. ECG Interpretation:

- AI-enhanced ECG interpretation software can analyze 12-lead ECGs with high sensitivity and specificity, automatically detecting subtle changes indicative of STEMI and differentiating them from non-ischemic ST-segment elevation.

- Deep learning algorithms trained on large ECG datasets can recognize patterns associated with specific coronary artery occlusions, aiding in the localization of the infarcted territory.

b. Cardiac Biomarker Analysis:

- AI algorithms can interpret serial cardiac biomarker measurements (e.g., troponin levels) and trend analysis to assess the kinetics of myocardial injury, predict infarct size, and guide therapeutic decisions.

- Machine learning models can incorporate additional clinical variables to enhance the diagnostic accuracy of cardiac biomarker testing and differentiate between STEMI and other causes of myocardial injury.

4. Treatment Decision-Making

a. Reperfusion Strategy Selection:

- AI-driven decision support systems can integrate patient-specific data, including clinical parameters, ECG findings, and time metrics, to guide the selection of reperfusion therapy (e.g., fibrinolytic therapy vs. primary PCI).

- Predictive analytics models can estimate the likelihood of successful reperfusion, procedural complications, and long-term outcomes to inform treatment decisions and optimize resource utilization.

b. Pharmacotherapy Optimization:

- AI algorithms can assist in tailoring pharmacotherapy regimens, including antiplatelet agents, anticoagulants, and adjunctive medications, based on individual patient characteristics, comorbidities, and risk profiles.

- Machine learning models can predict medication responses, adverse drug events, and drug interactions, enabling personalized therapeutic strategies and minimizing the risk of treatment-related complications.

5. Post-Reperfusion Care

a. In-Hospital Monitoring:

- AI-powered monitoring systems can analyze continuous physiological data streams, including vital signs, cardiac rhythms, and hemodynamic parameters, to detect early signs of complications (e.g., reinfarction, arrhythmias, heart failure).

- Machine learning algorithms can generate predictive models for in-hospital mortality, length of stay, and need for intensive care unit (ICU) admission, facilitating risk stratification and resource allocation.

b. Long-Term Management:

- AI-driven risk prediction models can evaluate long-term prognosis, estimate the likelihood of recurrent cardiovascular events, and inform secondary prevention strategies, such as lifestyle changes, medication adherence, and cardiac rehabilitation. Natural language processing (NLP) algorithms can extract structured data from clinical notes, discharge summaries, and follow-up reports to track disease progression, treatment response, and adherence to guideline-directed therapies.

Integrating Artificial Intelligence (AI) technologies into clinical decision-making processes holds the potential to revolutionize the management of ST-elevation myocardial infarction (STEMI) by offering timely, data-driven decision support throughout the continuum of care. From pre-hospital triage to long-term management, AI-driven algorithms can help healthcare providers identify high-risk individuals, expedite diagnosis and treatment, and optimize outcomes for STEMI patients. However, successfully implementing AI in STEMI care requires addressing challenges related to data interoperability, algorithm validation, regulatory compliance, and clinician acceptance. Collaborative efforts among clinicians, data scientists, industry stakeholders, and regulatory agencies are crucial for harnessing the full potential of Artificial intelligence (AI) holds promise for improving the standard of care for individuals with ST-elevation myocardial infarction (STEMI) in the future.

BACKROUND OF THE STUDY

The background of a study on an **Artificial Intelligence (AI)-based Clinical Decision Support System (CDSS) for Acute Emergency Care (AEC) of STEMI patients** based on standardized management protocol would likely encompass the following aspects:

Clinical Need of Work:

The important requirement for prompt and precise decision-making in the emergency treatment of patients with STEMI (ST-Elevation Myocardial Infarction) will be addressed by the study. STEMI is a serious kind of heart attack that needs to be treated right away since waiting too long might have a serious negative effect on the patient's prognosis. Despite medical advancements, STEMI remains one of the top 10 deadly illnesses worldwide in terms of burden one of the worst coronary-associated diseases that causes rapid cardiac death is STEMI. Providing comprehensive information on MI problems and creating a program to avoid MI appear to be essential.

In reference to WHO. Ischemic heart disease is the leading cause of death worldwide, accounting for 16% of all fatalities. This illness has caused the biggest rise in mortality since 2000, accounting for over 2 million of the 8.9 million deaths in 2019. The second and third most common causes of mortality, accounting for around 11% and 6% of all fatalities, respectively, are stroke and chronic obstructive pulmonary disease. (Wu, P., Yu, S., Wang, J., Zou, S., Yao, D.-S., & Xiaochen, Y. (2023). https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death. *Frontiers in Cardiovascular Medicine, 10*. https://doi.org/10.3389/fcvm.2023.1274663)

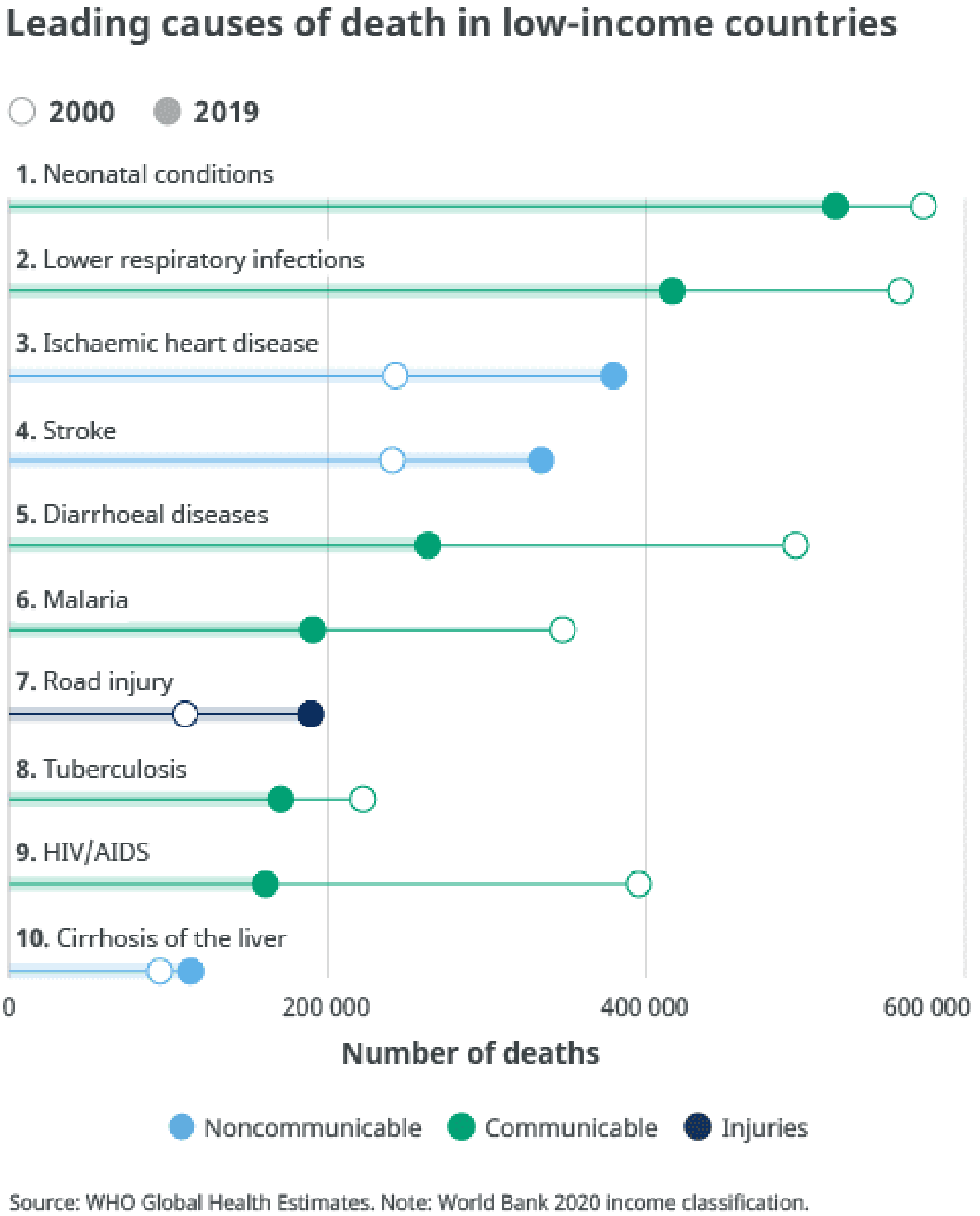

Figure 01: Global Health Estimates showing Ischemic Heart Disease as 3rd Leading cause of Death in countries with low income

At number four on the list of causes of mortality worldwide, lower respiratory infections continue to be the most fatal infectious disease. Nonetheless, the mortality toll has significantly decreased: in 2019, 2.6 million people died from it, 460 000 fewer than in 2000.

Approximately 126 million people (1,655 per 100,000) worldwide are affected with IHD, or 1.72% of the total population (Moran, A. E. (2018). Epidemiology and global burden of ischemic heart disease. *ESC CardioMed*, 297–304. https://doi.org/10.1093/med/9780198784906.003.0062). Worldwide, IHD was the cause of nine million fatalities. Compared to women, men were more frequently afflicted.

Global Burden of IHD: In 2019, young individuals (ages 25 to 49) accounted for 9.15% of ischemic heart disease (IHD) cases and 6.53% of IHD-related deaths worldwide. Over the past 30 years, there has been an increase in years lived with disability (YLDs) and prevalence of IHD among young people, but a decrease in mortality and disability-adjusted life years (DALYs) from 1990 to 2019. As inequality has risen, young adults in lower Socio-Demographic Index Countries (SDI) levels have experienced a disproportionately higher burden of IHD. The study underscores the need for effective strategies to reduce health disparities related to socioeconomic development and to alleviate the burden of IHD among young people. (Wu, P., Yu, S., Wang, J., Zou, S., Yao, D.-S., & Xiaochen, Y. (2023). Global burden, trends, and inequalities of ischemic heart disease among young adults from 1990 to 2019: A population-based study. *Frontiers in Cardiovascular Medicine, 10*. https://doi.org/10.3389/fcvm.2023.1274663)

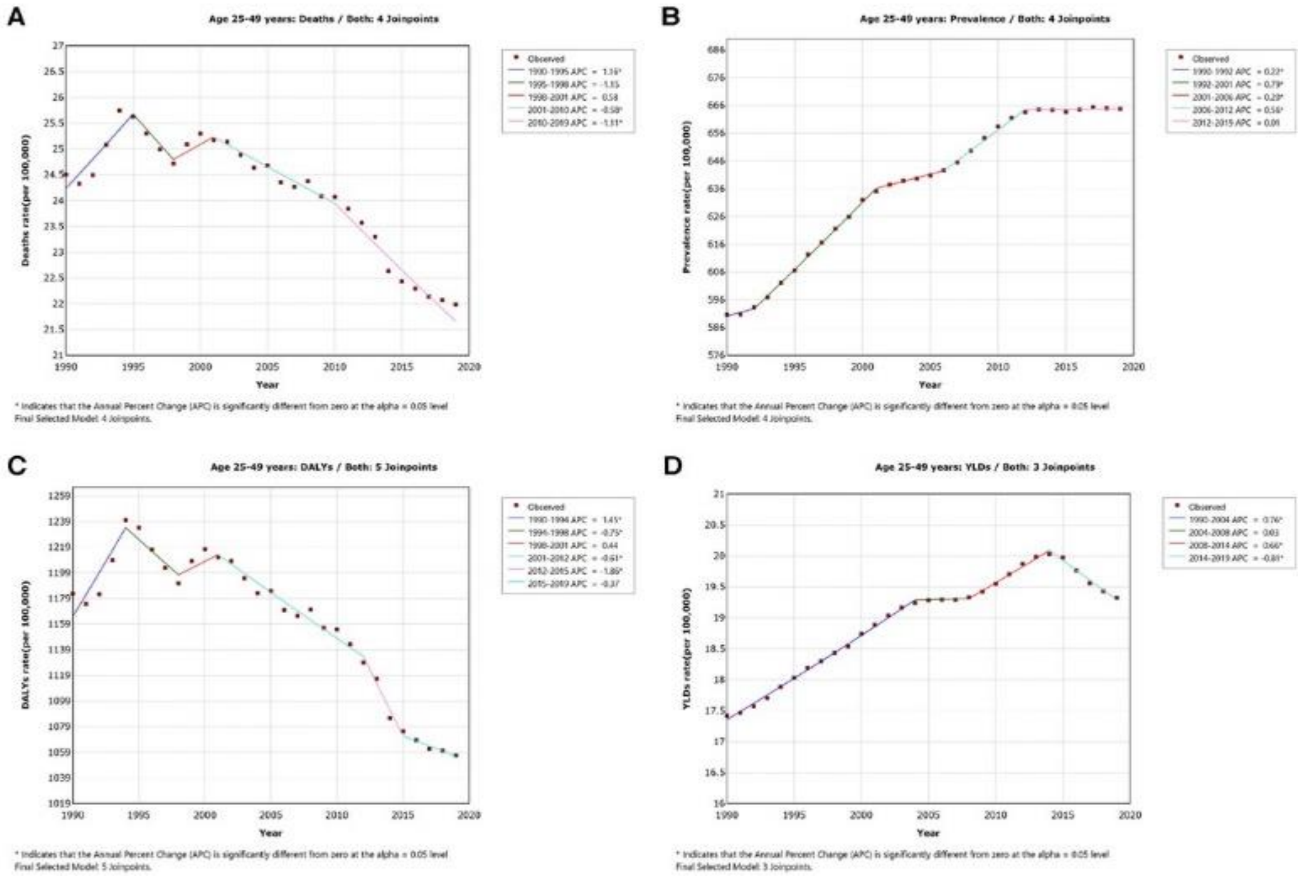

Figure 2: APC in IHD mortality (A), prevalence (B), disability-adjusted life-years (C), and years lived with disability (D) per 100, 000 populations among young adults globally from 1990 through 2019

Assumption of the Study

1. **Availability of Standardized Management Protocols**: The study assumes the existence of well-established and widely accepted standardized management protocols for the acute emergency care of STEMI patients. These protocols should be evidence-based, regularly updated, and endorsed by relevant medical organizations or regulatory bodies.

2. **Accessibility of Clinical Data**: The research presupposes the availability of extensive clinical data pertinent to the management of ST-elevation myocardial infarction (STEMI). This encompasses a wide range of information such as patient demographics, medical background, vital signs, laboratory findings, electrocardiograms (ECGs), cardiac imaging scans, and treatment responses. These datasets should ideally be accessible through electronic health records (EHRs) or other digital formats compatible with AI-driven analysis.

3. **Quality and Consistency of Data**: The study assumes the quality, accuracy, and consistency of clinical data used to train and validate the AI-based CDSS. Data integrity, completeness, and standardization are essential to ensure the reliability and generalizability of AI algorithms across different healthcare settings.

4. **Clinical Relevance of Endpoints**: The study assumes that the selected clinical endpoints or outcomes used to evaluate the effectiveness of the AI-based CDSS are clinically meaningful and aligned with the objectives of acute emergency care for STEMI patients. These endpoints may include time to reperfusion, door-to-balloon time, mortality rates, complication rates, and adherence to guideline-recommended therapies.

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5. **Clinician Engagement and Acceptance**: The study assumes active engagement and acceptance of the AI-based CDSS by healthcare providers involved in the acute emergency care of STEMI patients. Clinicians should be willing to integrate AI-driven decision support into their workflow and trust the recommendations provided by the system.

6. **Regulatory Compliance and Ethical Considerations**: The study assumes compliance with regulatory requirements and ethical standards governing the development, deployment, and evaluation of AI-based CDSS in healthcare settings. This includes adherence to data privacy regulations, informed consent procedures, and transparent reporting of AI algorithms' performance and limitations.

7. **Technical Infrastructure and Support**: The study assumes the availability of adequate technical infrastructure and support systems to implement and maintain the AI-based CDSS effectively. This includes access to high-performance computing resources, robust cybersecurity measures, and ongoing technical assistance for system optimization and troubleshooting.

8. **Cost-effectiveness and Resource Allocation**: The study assumes that the implementation of the AI-based CDSS for acute emergency care of STEMI patients is cost-effective and aligns with resource allocation priorities within healthcare organizations. Cost-benefit analyses and return on investment assessments may be conducted to evaluate the economic feasibility and sustainability of deploying AI technologies in clinical practice.

Integration Challenges and limitation:

Despite the potential benefits, there are obstacles in terms of system compatibility, data privacy, and clinician acceptance that need to be addressed. Integration challenges and limitations for implementing an Artificial Intelligence (AI) based Clinical Decision Support System (CDSS) for Acute Emergency Care (AEC) of ST-Elevation Myocardial Infarction (STEMI) patients based on standardized management protocols may include:

1. **Data Integration and Interoperability**: One of the primary challenges is integrating data from disparate sources such as electronic health records (EHRs), medical devices, and other health information systems. Variability in data formats, coding standards, and interoperability issues may hinder seamless integration, leading to incomplete or inconsistent data inputs for the AI-based CDSS.

2. **Data Quality and Completeness**: The accuracy, completeness, and reliability of clinical data are paramount for training and validating AI algorithms. However, data quality issues, including missing data, errors, and inconsistencies, compromised the performance of the CDSS and lead to biased or unreliable predictions. Ensuring data integrity and quality assurance processes are essential but may be challenging due to the sheer volume and complexity of clinical data.

3. **Algorithm Development and Validation**: Developing and validating AI algorithms for clinical decision support in acute emergency care requires rigorous methodology, robust validation studies, and regulatory compliance. Challenges arises in defining appropriate endpoints, selecting representative patient populations, and ensuring generalizability across diverse healthcare settings. Additionally, maintaining the performance of AI algorithms over time and adapting to evolving clinical practices pose ongoing challenges.

4. **Clinical Workflow Integration** Integrating the AI-based CDSS into existing clinical workflows and decision-making processes is critical for user acceptance and adoption. However, incorporating new technologies into established workflows may disrupt clinician routines, increase cognitive workload, and create resistance to change. Customizing the CDSS interface, providing user training, and fostering clinician engagement are essential strategies to overcome workflow integration challenges.

5. **Regulatory and Legal Compliance,** Adherence to regulatory mandates, privacy protocols, and ethical guidelines holds utmost importance during the implementation of AI-powered Clinical Decision Support Systems (CDSS) within healthcare environments. Meeting requirements outlined in laws like the Health Insurance Portability and Accountability Act (HIPAA) and obtaining necessary approvals from regulatory authorities can present intricate and lengthy processes. Effectively managing apprehensions regarding data

confidentiality, informed consent, liability issues, and risks of malpractice is essential for mitigating legal and ethical complexities.

6. **Resource Constraints and Cost Considerations**: Implementing and maintaining an AI-based CDSS requires significant financial investment, technical expertise, and organizational resources. Healthcare organizations may face budgetary constraints, staffing shortages, and competing priorities that limit their ability to deploy and sustain AI technologies effectively. Cost-benefit analyses, reimbursement models, and evidence of clinical utility are essential for demonstrating the value proposition of the CDSS and securing institutional support.

7. **User Acceptance and Trust**: Clinician acceptance and trust in AI-based CDSS are critical for successful implementation and utilization. Skepticism, perceived loss of autonomy, and distrust of AI-generated recommendations may impede user acceptance and adoption. Building trust through transparent communication, explaining AI algorithms' rationale and limitations, and soliciting feedback from end-users are essential strategies to enhance user acceptance and promote collaboration between humans and AI systems.

8. **Patient Engagement and Empowerment**: Involving patients in the decision-making process and promoting health literacy are integral to the success of AI-based CDSS. However, patient engagement may be challenging due to barriers such as limited health literacy, language barriers, and cultural differences. Designing user-friendly interfaces, providing educational resources, and involving patients in the development and testing of CDSS features can enhance patient engagement and empowerment.

Overcoming the obstacles and constraints associated with integrating AI in healthcare demands a collaborative effort across various disciplines, including healthcare providers, data scientists, technology suppliers, regulatory bodies, and patient advocates. Through proactive identification and mitigation of integration hurdles, healthcare institutions can harness AI advancements to bolster decision-making support, enhance patient results, and streamline resource allocation in acute emergency care for individuals with ST-elevation myocardial infarction (STEMI).

Standardized Protocols for STEMI:

It would emphasize the importance of standardized management protocols in ensuring that the AI-based CDSS provides consistent and reliable support across different healthcare settings.

Standardized protocols for ST-Elevation Myocardial Infarction (STEMI) management provide evidence-based guidelines to ensure consistent and optimal care for patients experiencing this acute cardiac event. These protocols encompass various aspects of care, including diagnosis, risk stratification, reperfusion therapy, adjunctive pharmacotherapy, and post-acute management. Here is an overview of the essential components: typically included in standardized protocols for STEMI management:

1. Pre-Hospital Assessment and Triage

1. Recognition and Pre-Hospital Management:

- Identify symptoms indicative of STEMI, such as chest pain or discomfort radiating to the arms, neck, or jaw.

- Activate emergency medical services (EMS) and promptly begin pre-hospital care.

- Utilize standardized tools, such as pre-hospital ECG acquisition and interpretation, to hasten the diagnosis and triage of STEMI patients.

2. Emergency Department Evaluation:

- Quickly assess and initially stabilize patients presenting with suspected STEMI.

- Perform a 12-lead electrocardiography (ECG) within 10 minutes of arrival to confirm the STEMI diagnosis.

- Apply standardized risk stratification tools, such as the TIMI (Thrombolysis in Myocardial Infarction) or GRACE (Global Registry of Acute Coronary Events) scores, to evaluate the patient's risk profile and guide management decisions.

3. Reperfusion Therapy:

- Choose the reperfusion strategy based on patient characteristics, time since symptom onset, and available resources:

  - Primary Percutaneous Coronary Intervention (PCI) for patients who present within the recommended time window and have access to a PCI-capable facility.

  - Fibrinolytic therapy for patients who present to non-PCI-capable hospitals or face delays in PCI activation.

- Adhere to door to balloon and door to needle time benchmarks to minimize treatment delays and optimize outcomes.

4. Adjunctive Pharmacotherapy:

- Administer antiplatelet agents (e.g., aspirin, P2Y12 inhibitors), anticoagulants (e.g., heparin, enoxaparin), and adjunctive medications (e.g., beta-blockers, statins) according to established guidelines.

- Customize pharmacotherapy based on individual patient characteristics, comorbidities, and contraindications.

5. **Post-Reperfusion Care**:

Continuous monitoring of vital signs, cardiac rhythm, and hemodynamic parameters to detect complications such as reinfection, arrhythmias, or heart failure.

Implementation of secondary prevention measures, including lifestyle modifications (e.g., smoking cessation, dietary changes, physical activity), medication adherence, and cardiac rehabilitation.

Timely initiation of guideline-directed medical therapy (GDMT) for secondary prevention, including beta-blockers, angiotensin-converting enzyme inhibitors (ACEIs) or angiotensin receptor blockers (ARBs), and statins.

6. **Follow-Up and Rehabilitation**:

Arrangement of timely follow-up visits with cardiology specialists for further risk assessment, medication optimization, and long-term management planning.

Referral to cardiac rehabilitation programs to promote physical rehabilitation, lifestyle modification, and psychosocial support for STEMI survivors.

7. **Quality Improvement and Performance Metrics**:

Implementation of quality improvement initiatives, including regular audit and feedback, performance benchmarking, and adherence to evidence-based practice guidelines.

Monitoring of key performance metrics, such as door-to-balloon time, reperfusion success rates, complication rates, and long-term outcomes, to evaluate the effectiveness of STEMI management protocols and identify areas for improvement.

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Standardized protocols for STEMI management serve as a framework for healthcare providers to deliver timely, evidence-based care and optimize outcomes for patients experiencing this life-threatening cardiac condition. These protocols are continuously updated based on evolving evidence, advances in technology, and quality improvement initiatives to ensure the highest standards of care delivery.

Summary of the model

This chapter covered the introduction to the study which highlighted key information ranging from the problem statement, background, key definitions, aims & objectives, limitations and need for work

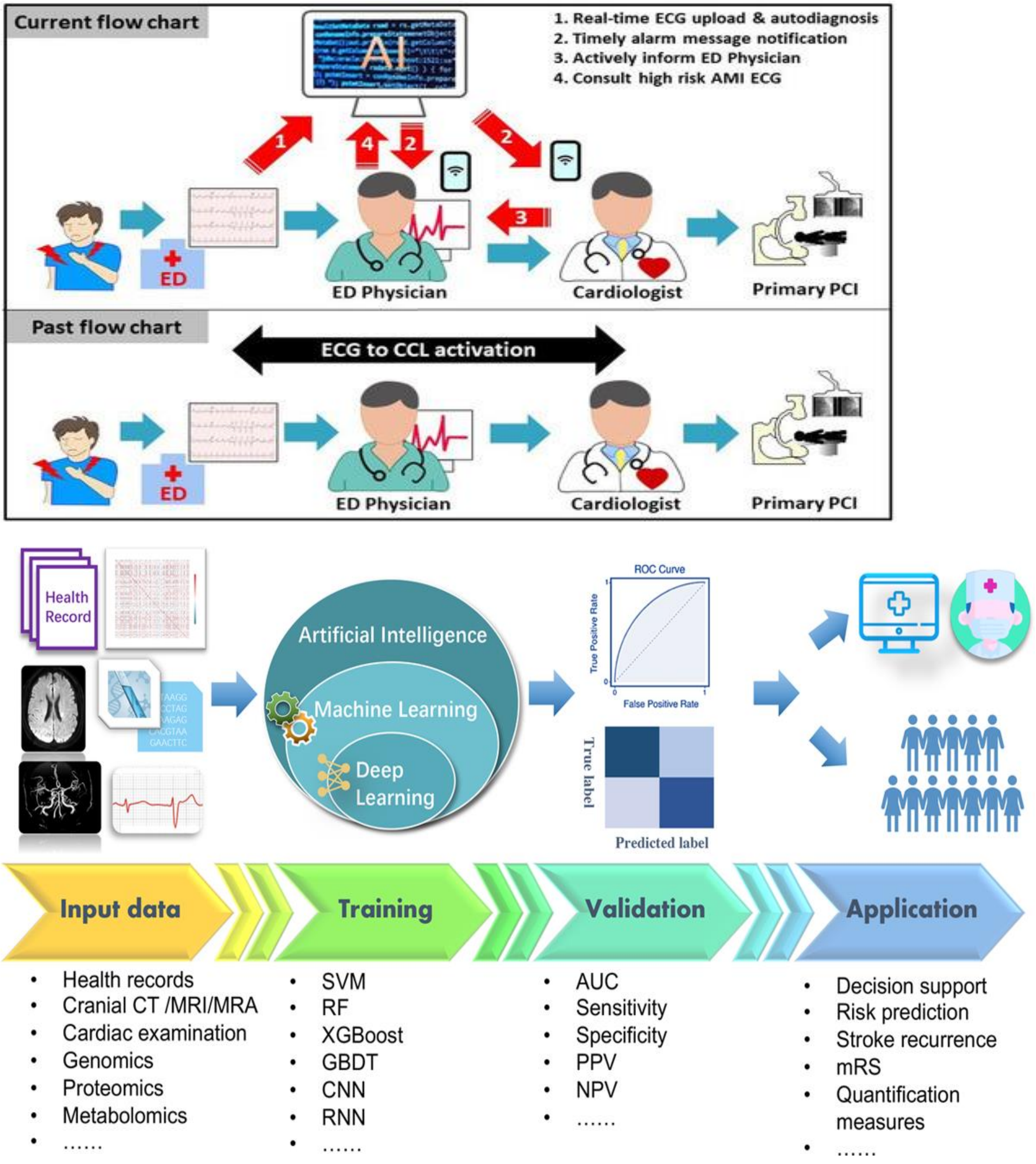

Figure 3: A and B shows the prototype of the AI model

AIMS AND OBJECTIVES

Aim: To develop an AI based model for Clinical Decision Support System of STEMI patients arriving at Emergency Department of a Tertiary care hospital.

OBJECTIVES:

1. **Development of an AI model for CDSS of STEMI in Hospital and Enhanced Diagnostic Accuracy:** Develop algorithms to rapidly and accurately identify STEMI cases based on ECG readings, symptoms, and patient data, reducing diagnostic errors and enabling quicker intervention. This serves as primary objective to develop and validate an AI-based CDSS
2. **Data Integration and Learning:** Ensure seamless integration with Electronic Health Records (EHRs) to access historical patient data, continuously learn from patient interactions, and refine decision-making algorithms through machine learning.
3. **Enhanced Healthcare Provider Support:** Provide decision support tools that aid healthcare providers in making timely and informed decisions, including treatment plans and intervention strategies.
4. **Quality Improvement and Research:** Enable data collection for quality improvement initiatives and research, facilitating ongoing improvement of emergency care protocols and advancing STEMI patient outcomes on a broader scale.

LITERATURE REVIEW

INTRODUCTION

Any research endeavor that looks at previously published information relating to a certain topic over a given period of time must include a literature review. Reviewing the body of knowledge already available on the topic is crucial to comprehending what is already

Known and pertinent, they offer a broad conceptual framework that can be used to contextualize the study problem.

Finding and analyzing material on a certain topic is the goal of research reviews, which are meant to provide readers with a thorough understanding of the subject. It detects significant conceptual and data-based knowledge on a given subject, highlights pertinent research questions within the area, and unearths fresh information that may be applied in a variety of ways to support or validate hypotheses.

Taylor and Procter, 2009 stated that in review of literature the researcher should apply the proposition of analysis to record the unbiased research studies, precisely the data sources to ensure discussion of pros and cons of each. Ultimately the major purpose of the review of literature is to establish values of prior research on the study topic

In reference to **Lobiondo wood and Haber.J, 2010** stated that a review of literature lays out a base for upcoming analysis. As a part of the task, it helps to establish research studies undertaking in the background of existing data base, which allows the researcher to become familiar with existing data

LITERATURE REVIEW related to this Study

Hilbert, A., Akay, E., Carlisle, B., Madai, V., Mutke, M., & Frey, D. (2022a). ***Artificial Intelligence for Clinical Decision Support in Acute Ischemic Stroke: A Systematic Review Ela Marie Z. Akay *; Adam Hilbert , MSc*; Benjamin G. Carlisle , PhD; Vince I. Madai , MD, PhD; Matthias A. Mutke , MD; Dietmar Frey , MD, JD.***

A total of 121 papers met the study inclusion criterion. Of these, 65 were determined to be fully extracted, 20 publications suggested an automated stroke grading system, and 36 studies suggested segmenting stroke lesions in imaging. The Supplementary Material contains an overview of the papers that recommend a lesion segmentation method. Of the twenty publications on automated stroke scoring, eighteen dealt with automated calculations of the Alberta Stroke Program Early CT Score, while two of the articles discussed automated techniques for generating collateral scores.

It draws attention to the transition from randomized trial-based generic treatment groups to artificial intelligence techniques that link patient attributes to treatment outcomes for individualized care.

Methodology -papers that suggested AI approaches for decision support in situations of acute ischemic stroke were the subject of a systematic review

The review's objectives were to outline the information and results that these systems employed, calculate the advantages they offered over conventional diagnosis and therapy, and document how well they complied with AI healthcare reporting guidelines

Bozyel, S. (2024). Artificial Intelligence-based clinical decision support systems in cardiovascular diseases. *The Anatolian Journal of Cardiology*, 74–86.

The paper examines the use of Clinical Decision Support Systems (CDSs) powered by Artificial Intelligence (AI) in the treatment of CVD6. These systems support healthcare practitioners in risk assessment, diagnosis, therapy optimization, and early warning of CVD events by leveraging AI approaches such as data analysis, prediction, and optimization.

Including AI-based CDSSs has the potential to enhance preventive cardiology treatment and optimize physician processes. However, the quality of the data and the participation of medical professionals in their review and training are key factors that determine how effective these systems are.

AI-based CDSSs have the potential to completely transform CVD patient care by giving medical professionals precise and individualized support. Sustained investigation and uniformity in data reporting are essential for the progress and incorporation of these systems into clinical use.

Bozyel, S. (2024). Artificial intelligence-assisted remote detection of ST-elevation myocardial infarction using a mini-12-lead electrocardiogram device in prehospital ambulance care. *The Anatolian Journal of Cardiology*, 74–86.

From the study an AI model efficiently analyzed 362 prehospital 12-lead ECGs from 275 patients who contacted fire station dispatch centers in Central Taiwan between July 2021 and March 2022 due to symptoms like shortness of breath or chest pain. Subsequent assessment of 335 additional ECGs showed that the AI responded to EMTs in ambulances in just 37.2 seconds on average, significantly faster than the response time of online physicians from 11 other fire stations without AI implementation (113.2 seconds ± 369.4, $P < 0.001$). To gauge the AI's overall performance in remotely detecting ST-elevation myocardial infarction (STEMI), various evaluation metrics such as accuracy, precision, specificity, recall, area under the receiver operating characteristic curve, and F1 score were computed, yielding impressive results with scores of 0.992, 0.889, 0.994, 0.941, 0.997, and F1 respectively.

ISC 2024: "Effect of an artificial intelligence-based clinical decision support system on stroke care quality and outcomes in patients with acute ischemic stroke (Golden Bridge II): A cluster-randomized clinical trial." (2024). *Blogging Stroke*.

Study included 18 years up 90 years old as Age Inclusion Criteria, classifying into (Adult to Adult Older) of all sexes with exclusion of heathy volunteers as exclusion criteria, it evaluated the efficacy of AI-based CDSS in reducing the risk on new clinical events i.e. Ischemic Strokes after 3 months,6 months, up to 12 months after initial symptoms onset the aim is to evaluate the efficacy of the tool in monitoring the risk factor for the new clinical events ie Cardiovascular disease (STEMI)

Chandrabhatla, A. S., Kuo, E. A., Sokolowski, J. D., Kellogg, R. T., Park, M., & Mastorakos, P. (2023, May 30). ***Artificial Intelligence and machine learning in the diagnosis and management of stroke: A narrative review of United States Food and Drug Administration-approved technologies*****. MDPI.**

FDA-Approved AI/ML Technologies: 22 AI/ML technologies, including diagnosis and rehabilitation, have received FDA approval for stroke management. These technologies help physicians by analyzing brain imaging data using sophisticated algorithms like convolutional neural networks.

Clinical Performance and Utility: It has been demonstrated that the evaluated technologies function similarly to neuroradiologists.

• They have a good effect on patient outcomes, such as fewer days spent in the neurological intensive care unit, and enhance clinical workflows by cutting down on the time it takes to read a scan.

Post-Stroke Rehabilitation: Neuromodulation techniques are used in the construction of two technologies for post-stroke rehabilitation.

Research Methodology: To find and assess the effectiveness of these technologies, the authors carried out a thorough search of FDA databases and literature.

The technology they highlighted had applications for intracerebral hemorrhage (ICH) and/or ischemic stroke. There are several FDA-approved AI/ML technologies that can help with improved stroke diagnosis and treatment. The essay highlights how these technologies have the potential to revolutionize stroke care and outlines the available research on the subject.

Gupta, S., Sharma, D. K., & Gupta, M. K. (n.d.). Artificial Intelligence in Diagnosis and Management of Ischemic Stroke.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards were adhered to this study during the review. The studies conducted from January 2018 to August 2022 that focused on AI/ML-based methods for keeping an eye on cardiovascular patients in intensive care units were included in the search. Deep learning, AI, ML, RL, clinical decision assistance, and cardiovascular critical care were among the search terms used. 89 studies were found after more than 100 searches using medical search engines. 21 studies were chosen for qualitative analysis following thorough evaluations. Common input modalities included clinical time series and data from electronic health records (EHRs). For analysis, techniques such as RL, RNNs, and gradient boosting were commonly employed.

Fujimori, R., Liu, K., Soeno, S., Naraba, H., Shirakawa, T., Hara, K., Sonoo, T., Ogura, T., Nakamura, K., & Goto, T. (2021). 135 acceptance and barriers of AI-based decision support systems in emergency departments: A quantitative and qualitative evaluation. ***Annals of Emergency Medicine*****,** ***78*****(4).**

Study done between March – April 2021 included transitional year hospital (n=6) emergency resident (n=8) and emergency physician (n=3) Study included 14 participants to measure the acceptance of AI Based clinical decision support system for acute emergency in emergency department. All participants completed questionnaires and interview, Quantitative analysis revealed that there is general positive for user acceptance

Fujimori, R., Liu, K., Soeno, S., Naraba, H., Shirakawa, T., Hara, K., Sonoo, T., Ogura, T., Nakamura, K., & Goto, T. (2021). Artificial intelligence-based clinical decision support in modern medical physics: Selection, acceptance, commissioning, and quality assurance. ***Annals of Emergency Medicine*****,** ***78*****(4).**

Context & Objectives: The integration of machine learning (ML) and artificial intelligence (AI) in clinical decision support systems (CDSSs) is the focus of this study.

The article highlights the potential advantages of CDSSs in the healthcare industry, including the potential to improve patient safety and save costs. It also highlights the risks that come with using insufficient or defective

CDSSs, which can lower healthcare quality and patient safety. The goal is to offer an organized method for implementing CDSSs, with a focus on machine and deep learning systems that covers selection, acceptance testing, commissioning, implementation, and quality assurance. A CDSS that complies with regional preferences and regulations requires a thorough selection procedure. Acceptance testing verifies that the CDSS complies with requirements and safety standards. Commissioning ensures that the CDSS operates appropriately and gets it ready for clinical use. The paper lists more than 60 references, demonstrating a thorough analysis of the body of literature. It discusses how CDSSs have changed since 1967, providing a historical viewpoint spanning more than 50 years. Different kinds of CDSSs, such as those based on rules, deep learning, probabilistic models, genetic algorithms, and reinforcement learning, are covered in the review. It cites particular instances of CDSSs, such the MYCIN system from the 1970s and the Leeds Abdominal Pain system from 1972. The authors draw the following conclusions: A methodical approach to the implementation of CDSS can reduce risks, improve patient safety, and raise the possibility of a successful integration into healthcare systems10. They support the ongoing review and revision of CDSSs in order to keep them accurate and relevant in the face of changing clinical procedures.

Directorate General of Health Services Ministry of Health & Family Welfare Government of India (Feb 17, 2021)

The goal of the study was to evaluate the temporal factors impacting the door-to-balloon time (D2B) in patients with acute ST-segment elevation myocardial infarction (STEMI). During the trial, the following timings were measured: consent, post-consent to balloon time (POSTCONSENT2B), ED to ECG, ED to coronary care unit (ED2CCU), and D2B. D2B was effective for 54 ± 12.2 min. Consent time and D2B showed a substantial positive connection ($\rho = 0.903$) among the dependent variables. This study reveals that consent time—a hitherto unidentified entity—significantly influences the D2B time.

J. Pers. Med. An Artificial Intelligence-Based Alarm Strategy Facilitates Management of Acute Myocardial Infarction. 2021, 11(11), 1149.

The effectiveness and practical applications of an advanced artificial intelligence (AI) model, akin to cardiologist expertise, in identifying acute myocardial infarction (AMI) through 12-lead electrocardiograms (ECGs) remain largely unexplored, despite its remarkable capabilities. To address this gap, we devised an AI-based alarm system (AI-S) for AMI detection. We formed a strategy development group comprising 25,002 patient visits from August 2019 to April 2020, along with a subsequent prospective validation group comprising 14,296 visits from May to August 2020, all within an emergency department setting. The AI-S incorporated inputs such as chest pain symptoms, 12-lead ECG readings, and high-sensitivity troponin I levels. Our primary objective was to gauge AI-S performance in the validation group by assessing its F-measure, precision, and recall. Additionally, we aimed to assess the impact of AI-S implementation on door-to-balloon (DtoB) time for patients with ST-segment elevation myocardial infarction (STEMI) undergoing primary percutaneous coronary intervention (PPCI). Notably, AI-S demonstrated precise detection of STEMI cases (F-measure = 0.932), achieving a precision and recall rate of 93.2%. This highlights its robustness in identifying critical cases.

Knoery, C. R., Heaton, J., Polson, R., Bond, R., Iftikhar, A., Rjoob, K., McGilligan, V., & Peace, A. (Year). Systematic Review of Clinical Decision Support Systems for Prehospital Acute Coronary Syndrome Identification.

Despite the diversity among studies, with marked differences that prevented a formal meta-analysis, the review identified eight studies meeting eligibility and quality standards out of 11,439 initially screened articles. Analysis of individual components revealed that patient history notably enhanced sensitivity and negative predictive values. Clinical Decision Support Systems (CDSS) incorporating all four components tended to exhibit higher sensitivities and negative predictive values. Additionally, CDSS incorporating computer-aided electrocardiogram diagnosis demonstrated higher specificities and positive predictive values. While the heterogeneity across studies precluded meta-analysis, this review underscores the promise of ACS CDSS in prehospital settings, particularly when patient history is considered alongside the integration of multiple components. The heightened sensitivity of certain components, combined with increased specificity, holds significant clinical implications.

Juang, W.-C., Hsu, M.-H., Cai, Z.-X., & Chen, C.-M. (2022). Developing an AI-assisted clinical decision support system to enhance in-patient holistic health care. ***PLOS ONE*****,** ***17*****(10).**

In mental health treatment research, artificial intelligence (AI) has been utilized to monitor patients and analyze their daily data to assess their mental well-being. Frangou *et al.* integrated AI into treatment by affixing a microelectronic sensor to the cap of a pill bottle. This sensor records and transmits timestamps each time the bottle is opened, allowing doctors to gauge medication adherence. Experimental results indicate the system effectively tracked patients' adherence to their prescription regimens. Additionally, Liu *et al.* developed a convolutional neural network (CNN) model to detect tuberculosis (TB) infection in X-ray images. The model's performance was evaluated on a dataset comprising 4701 X-ray images, with 453 classified as normal and 4249 as abnormal.

Artificial intelligence for clinical decision support for monitoring patients in cardiovascular ICUs: A systematic review Journal: Frontiers in Medicine

Volume: 10 Year: 2023

The comprehensive analysis in this study delves into the integration of machine learning and artificial intelligence within clinical decision support systems (CDS) tailored for cardiovascular intensive care units (ICUs). By adhering to established standards such as PRISMA and PICOS, it assesses the efficacy of AI/ML in augmenting clinician decision-making for patient monitoring in ICU settings. The review aims to identify advancements, challenges, and potential avenues for AI/ML applications in therapeutic contexts. To compile this review, the authors examined research published between January 2018 and August 2022, sourced from PubMed and Google Scholar. Utilizing a combination of keywords associated with AI, ML, and patient monitoring in cardiovascular care, relevant publications were retrieved. This exhaustive search yielded 89 studies from over 100 inquiries. Following rigorous technical and medical evaluations, key findings were synthesized.

MATERIAL AND METHODS

INTRODUCTION

This chapter covers all the details, including an explanation of the various procedures and methods used to gather samples and organize data. It covers the design, methodology, site, sample techniques, instrument construction and explanation, data collection, and analytic approach. The plan will include the rationale behind the research strategy, information about the setting and intended audience, methods for choosing study participants, the characteristics of those selected, the choice of data collection instruments, and the development of these instruments.

Through the use of thorough explanations and rational procedures for gathering data, analyzing it, and using statistical tools to find any significant findings, the research process will be highlighted.

The methodology employed in this study provides examples of common approaches to set up the procedure for getting reliable

SELECTION OF RESEARCH APPROACH

The tactics and procedures utilized to carry out the complete research project, from the fundamental presumptions to the minute details of sample collection, analysis, and interpretation, are known as research methodologies. During the research phase, this strategy entails a series of decisions that may be made in any sequence. The ultimate choices concern the methodology to be applied in order to explore the research subject.

A research strategy is often determined by the audiences for the study as well as the nature of the research topic or issues being addressed. The research strategy is a comprehensive plan or proposal that outlines the intersection of research ideas and particular procedures to be employed in the study. For the purpose of this study, the researcher will gather samples using a descriptive research methodology. Given that descriptive research focuses primarily on gathering, documenting, characterizing, and interpreting study-related data, it is a legitimate method of doing research for this project. Surveys are used, however they aren't only for gathering samples because they don't need any kind of measurement, comparison, analysis, or interpretation.

An observational research approach will help the investigator to pay close attention to every bit of the changes occurring during the entire process of sample collection over a period of time so that the investigator can obtain accurate information to interpret and analyze all record findings for the research. A qualitative approach is based on qualitative variables that can be quantified with suitable units. This will enable the investigator to use mathematical and statistical methods to derive the conclusions of their research. As this has a great benefit, also it can be used as the main way to examine all the data accumulated during the study which depends heavily on techniques for producing research findings. The researcher must be objective in order to obtain quantitative data from the research setting. This methodology can be evaluated quantitatively by using statistical methods

RESEARCH DESIGN

The study presented here is a Mixed Methods Study including both prospective sampling and retrospective sampling of clinical data.

RESEARCH SETTING

The selected study setting for prospective data collection was Emergency Department of Parul Sevashrum Hospital, Waghodia, Vadodara, Gujarat, India. The retrospective data set was collected from Kaggle repository which is an open access repository of data sets.

TARGET POPULATION

The target population in this study are all the patients presenting to the Emergency Department of Parul Sevashram Hospital with symptoms of Chest pain and are eventually diagnosed with STEMI. The study also covers the patients with previous known history of cardiovascular diseases or symptoms of an emerging cardiovascular disease. The target population was subjected to the following analysis:

1. **Demographics**: Characteristics such as age, gender, ethnicity, income level, education, and occupation.
2. **Geographic Location**: Specific locations such as cities, regions, countries, or even global populations.
3. **Specific Characteristics**: Traits or conditions that are pertinent to the study, such as patients with a certain disease, students in a particular grade level, or businesses of a specific size.
4. **Temporal Aspects**: Time-related factors like a particular period or duration relevant to the study.

SAMPLE SIZE OF THE STUDY

A suitable sample size of 250 patients present with sign of any Cardiovascular Disease, Chest Pain or Heart attack at Emergency Department during the study frame was used.

SAMPLING TECHNIQUE

We chose purposive sampling strategy to include the participants for the study based on our inclusion and exclusion criteria.

SELECTION CRITERIA:

INCLUSION CRITERIA:

1) Adult (Age 18-59) and Old (Age 60 or above),

2) Available during study period

3) Patients who are willing to participate

EXCLUSION CRITERIA:

1) Pregnant women with Hypertension

2) Hypertension with CKD patient

3) Pericarditis Patients with ST elevation ECG

DEVELOPMENT OF THE TOOL FOR DATA COLLECTION

The development of a tool for data collection is a process of collecting and measuring information about the variables of interest, in a proper way which enables the researchers answer to stated research question and allows the researcher to evaluate the results. Data collection tools are the instruments used to collect data such as questionnaires or interviews. The major aim of the data collection is to collect quality evidence that allows analysis to lead a reliable answer to research question.

During this study we came across various prior studies from which inspirations were drawn for tools design. A tool was designed based on the key words which may contribute to rule out possibilities of STEMI in patients taking treatment for Chest pain or presented sign and symptoms of Chest pain or Cardiovascular diseases at emergency department A detailed questionnaire as data collection tool was created by with investigator, which includes a series of questions for the purpose of collecting information from the target audience at Parul Sevashram Hospital, Waghodia, Vadodara, Gujarat. A total of 250 samples was selected for the study

VALIDITY OF THE TOOL

A research guide was followed in the creation of the instrument to ensure precise data collection and analysis. Various experts from the Parul Institute of Paramedical and Health Sciences, Parul Institute of Medical Science and Research, and Parul Sevashram Hospital, Waghodia, Vadodara, Gujarat, made the tool suitable in terms of validity by guiding the investigator through which characteristics are appropriate for the entire research project. To make sure the instrument was appropriate for the study, all necessary adjustments and research strategy preparation were carried out.

DATA ANALYSIS

The researcher intended to use a descriptive statistic to assess all of the data. Frequency distribution and percentage analysis were used to examine all the data, and the results were shown as tablets and graphs to illustrate how the study's overall results varied.

From the results, an incidence rate was computed to show the frequency of STEMI risk associated with STEMI in patients presented Symptoms of Chest pain or Cardiovascular Disease at Parul Sevashram Hospital, Waghodia, Vadodara, Gujarat.

RESULTS

INTRODUCTION

This chapter was comprehended to organize and summarize the data collected during research study for easy and accurate interpretation. the analysis and interpretation of all the data gathered from a total of 250 samples at Parul Sevashrum Hospital, Waghodia, Vadodara, Gujarat, will be covered in this chapter. Every piece of data that was gathered has been examined in light of the study's goals and objectives. The analysis's research results are referred to throughout the interpretation. It assisted the researcher in drawing conclusions based on data collected throughout the investigation.

The primary objective of this study is to develop and validate an Artificial Intelligence (AI)-based Clinical Decision Support System (CDSS) designed to enhance the acute emergency care (AEC) of patients suffering from ST-Elevation Myocardial Infarction (STEMI). This system will be based on standardized management protocols to ensure consistency and accuracy in clinical decision-making.

Primary Outcomes

- **Enhance Diagnosis and Triage**: Improve the accuracy and speed of diagnosing STEMI in acute emergency settings, ensuring timely and appropriate triage of patients.
- **Standardize Treatment Protocols**: Implement standardized treatment protocols within the AI-CDSS to provide uniform recommendations for the management of STEMI patients.
- **Optimize Resource Utilization**: Assist healthcare providers in optimizing the use of resources such as medication, equipment, and personnel during the management of STEMI.
- **Reduce Time-to-Treatment**: Decrease the time from patient presentation to the initiation of appropriate treatment (e.g., reperfusion therapy), which is critical for improving patient outcomes.
- **Improve Patient Outcomes**: Enhance overall patient outcomes by ensuring adherence to evidence-based guidelines and reducing the variability in clinical practice.
- **Facilitate Clinical Decision-Making**: Support healthcare providers in making informed and timely decisions by providing real-time, evidence-based recommendations.

Se**condary Outcomes**

- **Data Integration and Analysis**: Integrate and analyze patient data from various sources (e.g., electronic health records, imaging, lab results) to provide comprehensive clinical insights.
- **User Experience and Acceptance**: Assess the usability and acceptance of the AI-CDSS among healthcare providers in emergency care settings.
- **System Adaptability and Learning**: Ensure the AI-CDSS can adapt and learn from new data and evolving clinical guidelines to continuously improve its recommendations.
- **Cost-Effectiveness**: Evaluate the cost-effectiveness of implementing the AI-CDSS in acute emergency care settings.

Detailed Description of Outcomes

Enhance Diagnosis and Triage

- **Objective**: Develop algorithms to quickly and accurately diagnose STEMI from patient data, including ECG readings and clinical symptoms.

- **Outcome Measure**: Accuracy and speed of STEMI diagnosis compared to standard methods.

Standardize Treatment Protocols

- **Objective**: Incorporate evidence-based guidelines into the AI-CDSS to ensure consistent treatment recommendations.

- **Outcome Measure**: Adherence rates to standardized treatment protocols.

Optimize Resource Utilization

- **Objective**: Utilize AI to recommend efficient use of resources, minimizing waste and ensuring critical resources are available when needed.
- **Outcome Measure**: Resource utilization metrics before and after AI-CDSS implementation.

Reduce Time-to-Treatment

- **Objective**: Condensing the time from when a patient first arrives to when suitable treatments like thrombolysis or percutaneous coronary intervention (PCI) are initiated.
- **Outcome Measure**: Time-to-treatment intervals.

Improve Patient Outcomes

- **Objective**: Improve clinical outcomes such as mortality rates, complication rates, and recovery times by ensuring best practices are followed.
- **Outcome Measure**: Clinical outcome metrics, including mortality and complication rates.

Facilitate Clinical Decision-Making

- **Objective**: Provide real-time, actionable recommendations to clinicians to support decision-making processes.
- **Outcome Measure**: Clinician satisfaction and decision-making confidence

The major objective of this study is to develop and validate an AI-based CDSS that enhances the acute emergency care of STEMI patients by ensuring timely, accurate, and standardized clinical decision-making. By achieving these objectives, the study aims to improve patient outcomes, optimize resource utilization, and provide a valuable tool for healthcare providers in emergency care settings.

ASSUMPTIONS OF THE STUDY

1. Data Quality and Availability

- **Assumption**: High-quality, comprehensive, and accurate patient data will be available from electronic health records (EHRs), ECG readings, and other relevant clinical sources.
- **Rationale**: The AI-CDSS relies on accurate and detailed data to provide precise recommendations. Incomplete or erroneous data could lead to incorrect or suboptimal decisions.

2. Adherence to Standardized Protocols

- **Assumption**: The standardized management protocols used to train the AI-CDSS are current, evidence-based, and widely accepted within the medical community.
- **Rationale**: For the AI-CDSS to be effective, it must base its recommendations on reliable and validated guidelines.

3. User Competence and Training

- **Assumption**: Healthcare providers using the AI-CDSS will have received adequate training on how to use the system effectively.

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- **Rationale**: Proper training ensures that clinicians can interact with the AI-CDSS correctly and interpret its recommendations appropriately.

4. Technology Integration

- **Assumption**: The AI-CDSS can be seamlessly integrated into the existing healthcare IT infrastructure without significant technical issues.
- **Rationale**: Smooth integration is necessary for real-time data processing and decision support, which are critical in acute emergency care settings.

5. Timely Data Entry

- **Assumption**: Clinicians will enter patient data into the system in a timely manner, ensuring that the AI-CDSS has the most current information to base its recommendations on.
- **Rationale**: Delays in data entry could lead to outdated or incorrect recommendations, potentially impacting patient outcomes.

6. Ethical and Legal Compliance

- **Assumption**: The development and implementation of the AI-CDSS will comply with all relevant ethical guidelines and legal regulations, including patient privacy and data security standards.
- **Rationale**: Ensuring compliance is critical to maintaining patient trust and avoiding legal issues that could hinder the study.

7. Acceptance and Trust

- **Assumption**: Clinicians will accept and trust the AI-CDSS, using its recommendations to guide their clinical decisions.
- **Rationale**: The effectiveness of the AI-CDSS depends on its acceptance by end-users, as resistance or skepticism could reduce its impact on clinical practice.

8. Consistency and Reliability

- **Assumption**: The AI algorithms used in the CDSS will consistently and reliably interpret patient data and generate accurate recommendations.
- **Rationale**: Consistent and reliable performance is essential for the AI-CDSS to be trusted and relied upon in critical situations.

9. Generalizability of Training Data

- **Assumption**: The training data used to develop the AI-CDSS is representative of the patient population it will be applied to, covering a wide range of clinical scenarios.
- **Rationale**: For the AI-CDSS to be broadly applicable, it must be trained on data that reflects the diversity and variability of real-world clinical cases.

10. Continuous Improvement and Learning

- **Assumption**: The AI-CDSS will have mechanisms for continuous learning and improvement, incorporating new data and evolving clinical guidelines over time.
- **Rationale**: Continuous learning is necessary to ensure that the AI-CDSS remains up-to-date and improves its performance as more data becomes available.

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These assumptions form the foundation upon which the study is designed and implemented. They ensure that the AI-based CDSS can be effectively developed, validated, and integrated into clinical practice to enhance the acute emergency care of STEMI patients. Addressing and validating these assumptions is critical for the success and reliability of the study outcomes.

ORGANIZATION OF THE DATA

1. Correlation matrix to examine the relationships between the Variables and the target variable (ST-ELEVATION MYOCARDIAL INFARCTION`)

2. To facilitate accurate analysis, the investigator organized everything using a tablet to list the following:

• Distribution of selected features relative to the target variable.

• The correlation matrix of Random forest to test model accuracy with reduction of some Variables.

ANALYSIS AND INTERPRETATION OF THE DATA FOR THE SAMPLES.

Overview

This project aimed to develop a predictive model for detecting cases of ST-Elevation Myocardial Infarction (STEMI) through the analysis of patient data. The dataset utilized for this endeavor was obtained from.

Title: Heart Disease Explainable CatBoost 100% Recall Repository: Kaggle https://www.kaggle.com/code/dkson1/heart-disease-explainable-catboost-100-recall/input which contained 55 features and 15757, including demographic information, medical history, and test results. The project encompassed several key stages: data preprocessing, feature engineering, model training, evaluation, and visualization. Below is a detailed description of each phase, the tools used, and the outcomes achieved.

Data Integration and Preprocessing

1.Data Collection:

- We utilized a dataset comprising various features indicative of Coronary Artery Disease (CAD). These features were categorized into four groups: demographic, symptom and examination, laboratory and echo, and ECG features. This dataset served as the foundation for our predictive model.

2. Data Cleaning:

- Handling Missing Values: Missing values were addressed through imputation. For numerical features, missing values were replaced with the mean or median of the column. For categorical features, the most frequent category was used. This step ensured that our dataset was complete and suitable for model training.
- Categorical Encoding: We converted categorical variables into numerical formats using encoding techniques. Label encoding and one-hot encoding were employed to transform categorical data into a form suitable for machine learning algorithms. This process involved converting categories like gender, admission type, and urban/rural status into numerical values.

3. Feature Engineering:

Numerical Encoding: The `ST Elevation ECG` column was encoded into numerical values using `LabelEncoder` from scikit-learn, converting categorical ECG states into numerical values for model compatibility.

4. Correlation Analysis:

- We computed the correlation matrix to examine the relationships between the Variables and the target

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variable (`ST ELEVATION MYOCARDIAL INFARCTION`). This analysis helped identify features with strong correlations to the target, guiding feature selection for model training.

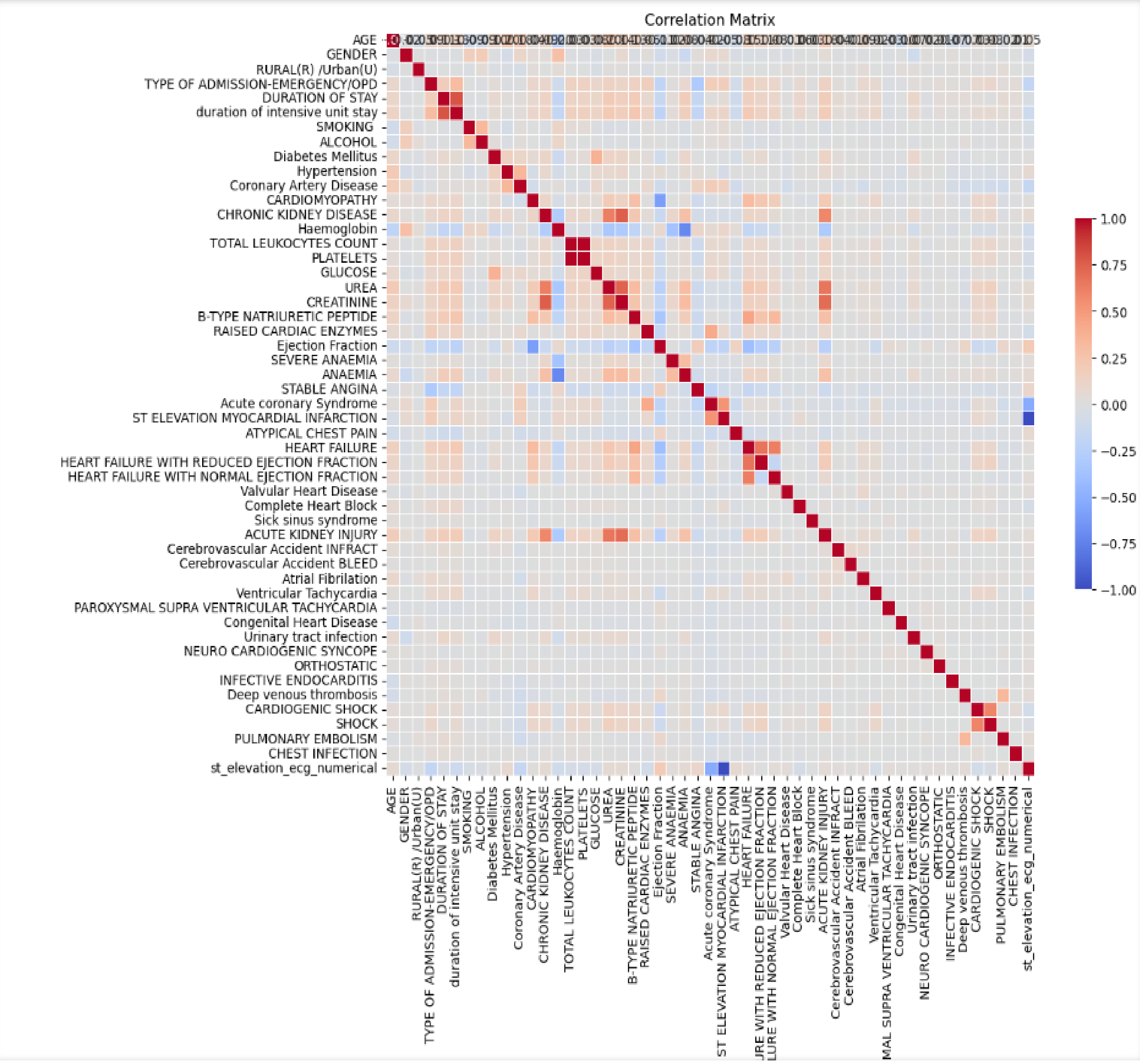

Figure 4: The correlation matrix to examine the relationships between the Variables and the target variable (`ST ELEVATION MYOCARDIAL INFARCTION`)

5. Proportions and Intervals Analysis:

- We analyzed the proportion of non-binary features that resulted in positive STEMI outcomes. For instance, we identified intervals of BNP values associated with positive results, providing insights into how specific ranges of certain features correlate with STEMI occurrences.

Model Training and Evaluation

1. Feature Selection:

- We selected relevant features for model training, focusing on attributes likely to influence STEMI prediction. The selected features included `AGE`, `GENDER`, `SMOKING`, `ALCOHOL`, `Diabetes Mellitus`,

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`Hypertension`, `Coronary Artery Disease`, `ST ElevationECG `, `RAISED CARDIAC ENZYMES`, `Complete Heart Block`, `Sick sinus syndrome`, `ACUTE KIDNEY INJURY`, `Cerebrovascular Accident INFRACT`, `Ventricular Tachycardia`, `Congenital Heart Disease`, `Urinary tract infection`, `ORTHOSTATIC`, `Deep venous thrombosis`, `CARDIOGENIC SHOCK`, and `SHOCK`.

Before choosing these features, based on the correlations matrix we iteratively removed some feature in order to get less features to process for the model. Following are some screenshots for the features used and their accuracies:

```
# Selecting columns for X (features)
X = df[['AGE', 'GENDER', 'RURAL(R) /Urban(U)',
        'TYPE OF ADMISSION-EMERGENCY/OPD', 'DURATION OF STAY',
        'SMOKING ', 'ALCOHOL',
        'Diabetes Mellitus', 'Hypertension', 'Coronary Artery Disease',
        'CARDIOMYOPATHY', 'CHRONIC KIDNEY DISEASE', 'Haemoglobin',
        'TOTAL LEUKOCYTES COUNT', 'PLATELETS', 'GLUCOSE', 'UREA', 'CREATININE',
        'B-TYPE NATRIURETIC PEPTIDE', 'RAISED CARDIAC ENZYMES',
        'st_elevation_ecg',
        'ANAEMIA', 'STABLE ANGINA',
        'Acute coronary Syndrome','HEART FAILURE',
        # 'HEART FAILURE WITH REDUCED EJECTION FRACTION',
        # 'HEART FAILURE WITH NORMAL EJECTION FRACTION',
        'Valvular Heart Disease',
        'Complete Heart Block', 'Sick sinus syndrome', 'ACUTE KIDNEY INJURY',
        'Cerebrovascular Accident INFRACT',
        'Atrial Fibrilation', 'Ventricular Tachycardia','Congenital Heart Disease',
        'Urinary tract infection', 'ORTHOSTATIC',
        'Deep venous thrombosis', 'CARDIOGENIC SHOCK',
        'SHOCK', 'CHEST INFECTION']]

# Selecting 'ST ELEVATION MYOCARDIAL INFARCTION' as y (target variable)
y = df['ST ELEVATION MYOCARDIAL INFARCTION']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train random forest classifier
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_train, y_train)

#  models evaluation

rf_preds = rf_clf.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_preds)

print("Random Forest Accuracy:", rf_accuracy*100)
```

```
Random Forest Accuracy: 92.38578680203045
```

Figure 5 Algorithms forest Captured after reduction of possible variables showing to test the accuracy of prediction 92% Accurate

CHEST INFECTION, CARDIOMYOPATHY, Urinary tract infection, HEART FAILURE WITH NORMAL EJECTION FRACTION, CREATININE, UREA, ANAEMIA, STABLE ANGINA.

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```
[9]: X1 = df[['AGE', 'GENDER', 'RURAL(R) /Urban(U)',
        'TYPE OF ADMISSION-EMERGENCY/OPD',
        'SMOKING ', 'ALCOHOL',
        'Diabetes Mellitus', 'Hypertension', 'Coronary Artery Disease',
        'Haemoglobin',
        'TOTAL LEUKOCYTES COUNT', 'PLATELETS', 'GLUCOSE', 'UREA', 'CREATININE',
        'B-TYPE NATRIURETIC PEPTIDE', 'RAISED CARDIAC ENZYMES',
        'st_elevation_ecg',
        'ANAEMIA',
        'Acute coronary Syndrome','HEART FAILURE',
        'Valvular Heart Disease',
        'Complete Heart Block', 'Sick sinus syndrome', 'ACUTE KIDNEY INJURY',
        'Cerebrovascular Accident INFRACT',
        'Atrial Fibrilation', 'Ventricular Tachycardia','Congenital Heart Disease',
        'Urinary tract infection', 'ORTHOSTATIC',
        'Deep venous thrombosis', 'CARDIOGENIC SHOCK',
        'SHOCK']]



# Selecting 'ST ELEVATION MYOCARDIAL INFARCTION' as y (target variable)
y1 = df['ST ELEVATION MYOCARDIAL INFARCTION']



X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.2, random_state=42)


# Train random forest classifier
rf_clf1 = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf1.fit(X_train1, y_train1)


rf_preds1 = rf_clf1.predict(X_test1)
rf_accuracy1 = accuracy_score(y_test1, rf_preds1)


print("Random Forest Accuracy:", rf_accuracy1*100)

Random Forest Accuracy: 92.16370558375635
```

Figure 6 Algorithms Random forest Captured after reduction of possible variables showing to test the accuracy of prediction remained 92% Accurate

CHEST INFECTION, CARDIOMYOPATHY, Urinary tract infection, Atrial Fibrilation, HEART FAILURE, Valvular Heart Disease, Cerebrovascular Accident INFRACT, HEART FAILURE WITH NORMAL EJECTION FRACTION, ACUTE KIDNEY INJURY, CREATININE, UREA, CHRONIC KIDNEY DISEASE, ANAEMIA, STABLE ANGINA

```
X2 = df[['AGE', 'GENDER', 'RURAL(R) /Urban(U)',
        'TYPE OF ADMISSION-EMERGENCY/OPD',
        'SMOKING ', 'ALCOHOL',
        'Diabetes Mellitus', 'Hypertension', 'Coronary Artery Disease',
        'Haemoglobin',
        'TOTAL LEUKOCYTES COUNT', 'PLATELETS', 'GLUCOSE', 'UREA', 'CREATININE',
        'B-TYPE NATRIURETIC PEPTIDE', 'RAISED CARDIAC ENZYMES',
        'st_elevation_ecg',
        'ANAEMIA',
        'Acute coronary Syndrome',
        'Complete Heart Block', 'Sick sinus syndrome', 'ACUTE KIDNEY INJURY',
        'Cerebrovascular Accident INFRACT',
        'Ventricular Tachycardia','Congenital Heart Disease',
        'Urinary tract infection', 'ORTHOSTATIC',
        'Deep venous thrombosis', 'CARDIOGENIC SHOCK',
        'SHOCK']]

# Selecting 'ST ELEVATION MYOCARDIAL INFARCTION' as y (target variable)
y2 = df['ST ELEVATION MYOCARDIAL INFARCTION']



X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.2, random_state=42)


# Train random forest classifier
rf_clf2 = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf2.fit(X_train2, y_train2)


rf_preds2 = rf_clf2.predict(X_test2)
rf_accuracy2 = accuracy_score(y_test2, rf_preds2)


print("Random Forest Accuracy:", rf_accuracy2*100)

Random Forest Accuracy: 91.87817258883248
```

Figure 7: Algorithm Random Forest Captured after Futher reduction more of possible variables showing to test the accuracy of prediction became 91% Accurate

2. Splitting the Data:

- The dataset was split into training and testing sets using an 80-20 split, ensuring the model was trained on a substantial portion of the data while reserving a portion for evaluating model performance on unseen data.

3. Model Training:

- Decision Tree Classifier: We trained a Decision Tree Classifier using the `DecisionTreeClassifier` from scikit-learn. This model was chosen for its simplicity and interpretability.

- Random Forest Classifier: We also trained a Random Forest Classifier using the `RandomForestClassifier` from scikit-learn. This ensemble method constructs multiple decision trees and merges them to improve prediction accuracy and stability.

Random Forest is an ensemble learning method primarily used for classification and regression tasks. It builds multiple decision trees during training and merges them to get more accurate and stable predictions. Here's how it works:

1.Bagging: Random Forest uses a technique called bagging (Bootstrap Aggregating). It generates multiple subsets of the training data by sampling with replacement. Each subset is used to train a separate decision tree.

2. Feature Randomness: While splitting nodes during the construction of each decision tree, Random Forest only considers a random subset of features. This introduces additional randomness, helping to create diverse trees.

3. Aggregation: After all trees are trained, Random Forest makes predictions by averaging the predictions of the individual trees (for regression) or by taking a majority vote (for classification).

The advantages of Random Forest include:

- Improved Accuracy: By combining the results of multiple trees, Random Forest often achieves higher accuracy than individual decision trees.

- Reduced Overfitting: The ensemble approach reduces the risk of overfitting, making the model generalize better to unseen data.

- Feature Importance: Random Forest provides insights into feature importance, helping identify which features contribute most to the predictions.

4. Model Evaluation:

- Predictions were made on the test set, and model accuracy was evaluated using the `accuracy_score` and the confusion matrix metric from scikit-learn.

The results are as follow:

- The Decision Tree Classifier achieved an accuracy of [specific value].

- The Random Forest Classifier achieved an accuracy of 92.2%, making it the most effective model for predicting STEMI in our dataset.

Data Visualization

1. Bar Plot:

- To visualize the distribution of selected features relative to the target variable (STEMI), we created bar plots. This visualization method provided an intuitive representation of feature distributions and their associations with STEMI outcomes.

Examples:

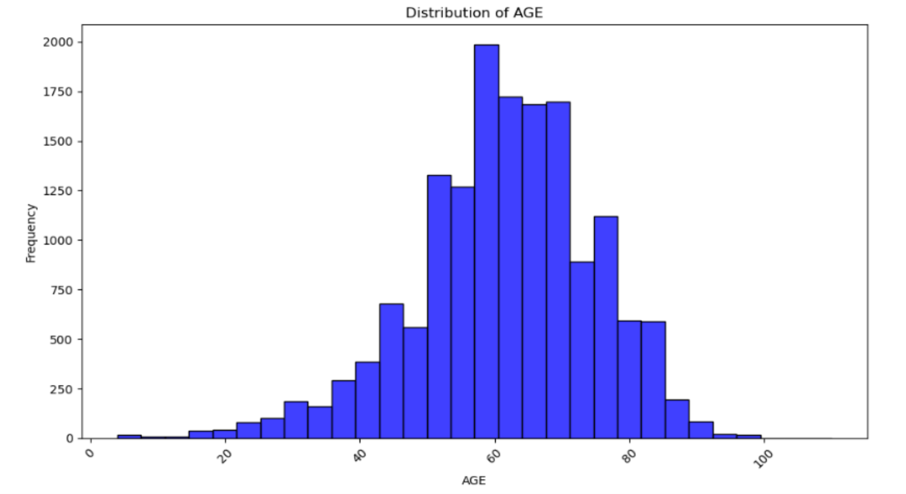

Figure 8 The Graph of distribution of selected features relative to the target variable (STEMI), AGE

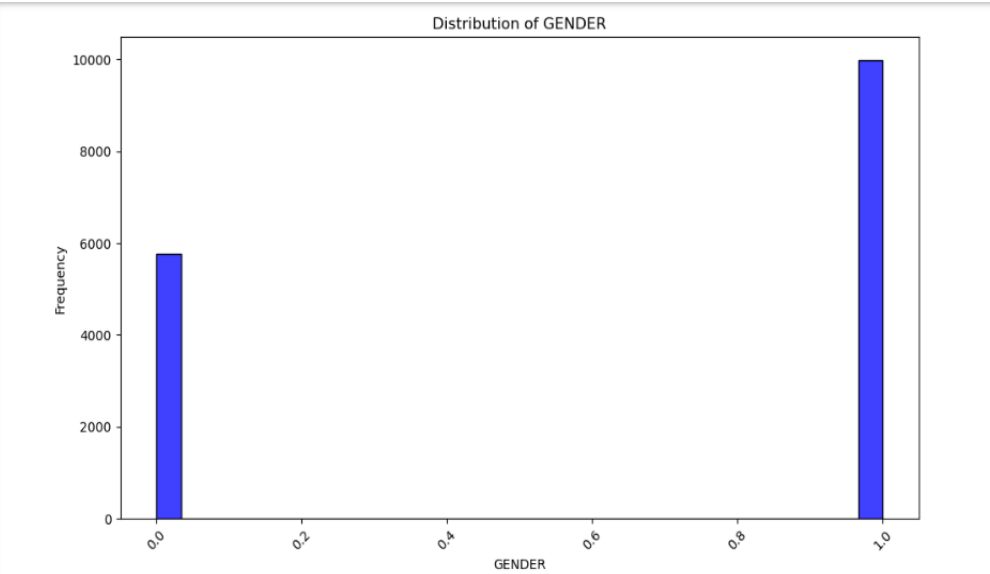

Figure 9 The Graph of distribution of selected features relative to the target variable (STEMI), Gander

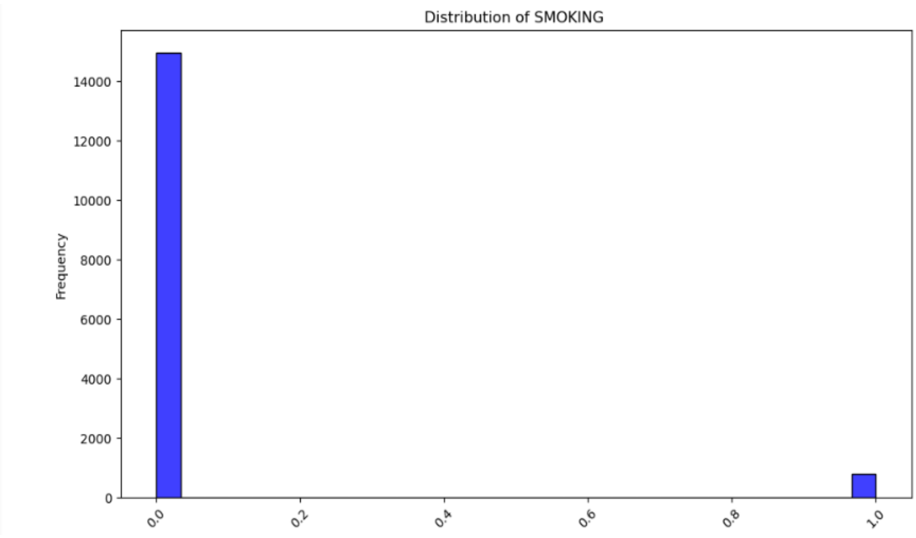

Figure 10 The Graph of distribution of selected features relative to the target variable (STEMI), Smoking

- We utilized `matplotlib` and `seaborn` libraries for generating these plots.

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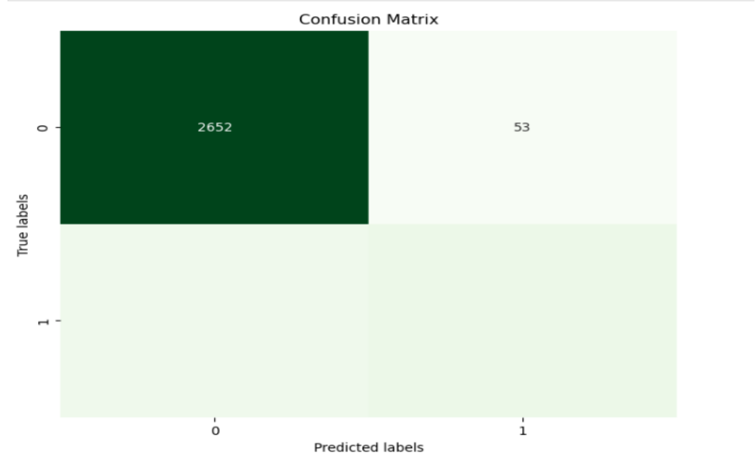

Figure 11 The Graph matplotlib` and `seaborn libraries for generating these plots

AI BASED CLINICAL SUPPORT DECISION SYSTERM ALGORITHIMS FOR STEMI

PREDICTION MODEL

FLOW CHART

PATIENT ARIVAL IN EMERGENCY DEPARTMENT (E.M.D)

PHYSICAL ASSMENT

UNCOUSIOUS PATIENT AT E.M.D /OUTSIDE E.M.D

CLINICAL FEATURES MANIFESTATION (AI SHOULD RECOMMEND ASSESMENT IN <2M)

Breathlessness (YES/NO –if yes suggest MI present)

Collapse (YES/NO if yes suggest MI present)

Carotid Pulse (PRESENT/ NOT if not Present suggest MI presents plus cardiac arrest)

AI RECOMMEND: IMMEDIATE START CPR AND ACLS PROTOCOLS

AI SHOUL RECOMMEND: INVESTIGATION TO BE DONE IN <10 MIN

1. ECG (ST ELEVATION ABOVE 1MM OR DEPRESSION ABOVE 1MM)
2. ENZYMES

ENZYMES	NORMAL VALUE	ELEVATED
Troponin I/T	<60ng/h	Above normal Suggest MI
CPK·MB	4·6%ofCPK	Above normal Suggest MI
CPK	25·90U/I	Above normal Suggest MI
LDH	45-90U/ml	Above normal Suggest MI
SGOT	0-35 U/L	Above normal Confirm MI

Table 1: Values of Cardiac enzyme’s common Used in Prediction of Myocardial Ischemia

CONSCIOUS ARRIVED AT E.M.D
Take patient History and full examination
Physical assessment

Pain in chest (a) Onset/not onset- onset confirm MI
(b) Radiating/not radiating- Radiating suggest MI
Breathlessness (present with pain/present without pain-present with pain can suggest MI
Vomiting (Present/not- if present suggest sever MI)
Pulse: (feeble pulse/NOT feeble pulse- feeble pulse suggest MI)
Heart sound: (Muffled sound/not-muffled sound suggest MI)
AI should suggest (to be done in less than 10 min)

To give Aspirin medicine and consider oxygen Nitroglycerin and morphine if needed
Obtain 12 ECG leads
Obtain initial Cardiac Biomarkers(Enzymes)

INTERPRETATION/CONFIRMATION

1.ST ELEVATION IN ECG LEADS - Confirmed STEMI
(ST ELEVATION ABOVE 1MM)
2.CHANGES IN ENZYME LEVELS (ELEVATION)

Rush a patient for Reperfusion and Heparin

1.ST Depression- Confirmed - NSTEMI
(DEPRESSION BELOW 1MM)
2.TROPONIN-I ELEVATION
WITHOUT ECG CHANGES

Determine Risk Factor and give Aspirin

Flow chart showing the summarized AI prediction model for STEMI

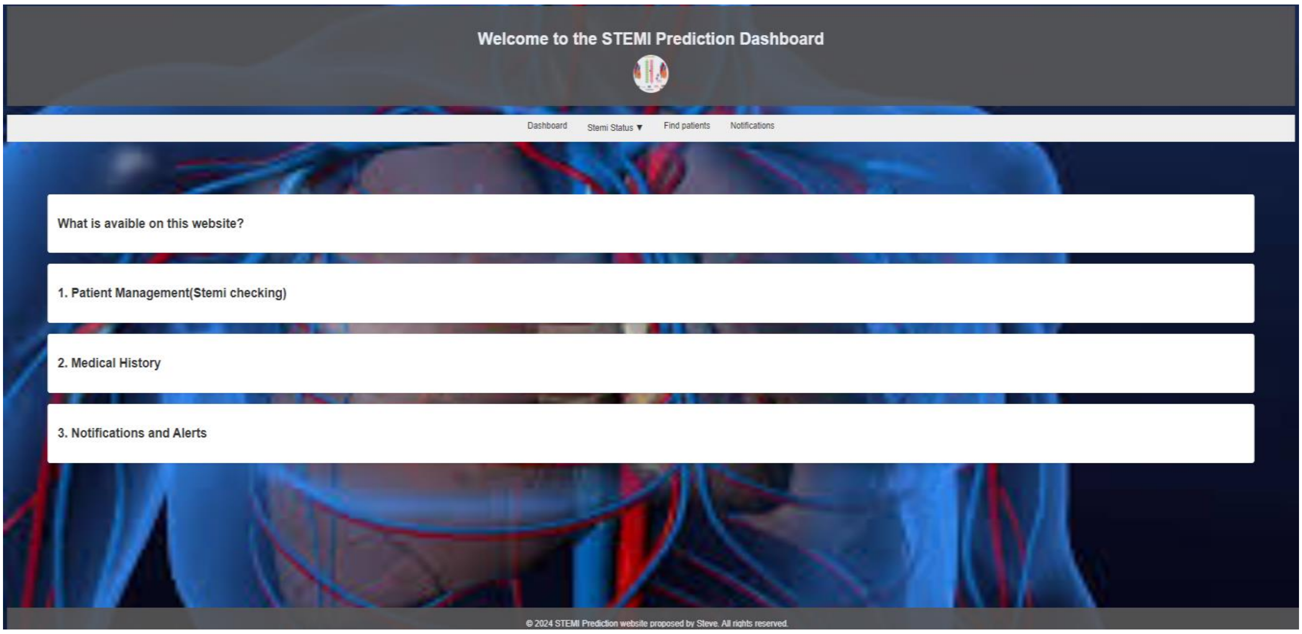

Image:5- Dashboard of Developed STEMI Prediction tool

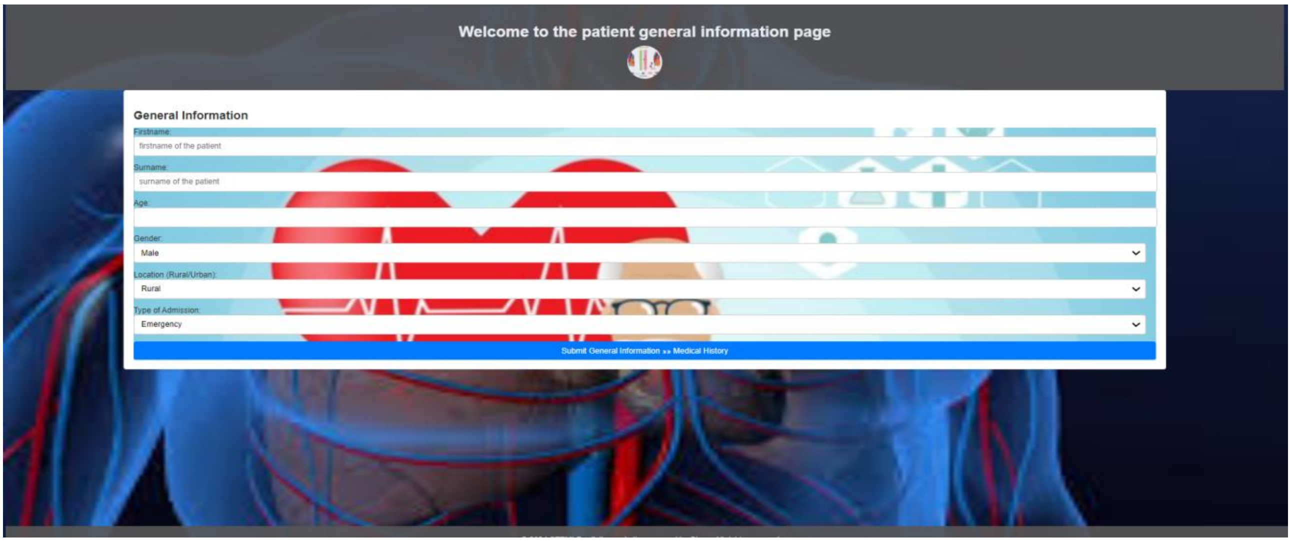

Image:6- Prediction tool for Conscious patient information dashboard

Image:7- Prediction tool, the dashboard for Unconscious Patient

Tools and Libraries

- Pandas: For data manipulation and analysis. Pandas provided the necessary data structures and functions to clean and prepare the data effectively.
- Numpy: For numerical operations and handling arrays, enabling efficient computation and data manipulation.
- Scikit-learn: For implementing machine learning algorithms, including decision trees and random forests, and for model training and evaluation.
- Matplotlib and Seaborn: For data visualization, allowing us to create informative plots and charts to understand data distributions and model results.
- LabelEncoder: From scikit-learn, used for encoding categorical variables into numerical values, making them suitable for machine learning algorithms.

CONCLUSION

The development of this predictive system involved comprehensive steps from data integration and preprocessing to model training and evaluation. By carefully handling missing values, encoding categorical variables, and selecting relevant features, we built a model capable of predicting STEMI with high accuracy. The Random Forest Classifier, in particular, provided the best performance with an accuracy of 92.2%. The use of visualizations helped in understanding data distributions and feature importance. The final system offers valuable insights for identifying potential STEMI cases based on patient data, demonstrating the efficacy of machine learning in medical diagnostics.

DISCUSSION

This chapter provides information on the key results, recommendations, consequences, and summary of the research. The researcher will review and analyze the data analysis chapter's results in this chapter, and they will also provide a conclusion on the study's findings.

Summary:

The research aims to develop and implement an AI-based CDSS that integrates standardized management protocols for STEMI patients to improve the accuracy, consistency, and timeliness of emergency care, ultimately leading to better patient outcomes and more efficient healthcare delivery. To enhance the quality and efficiency of emergency care for STEMI patients by leveraging AI technologies this is to help in following:

Improving Diagnosis Accuracy and Speed:

Utilizing AI algorithms to quickly and accurately identify STEMI from patient data, such as ECG results and clinical symptoms.

Reducing the time to diagnosis, which is critical in improving patient outcomes in STEMI cases.

Standardizing Care Protocols:

Implementing standardized management protocols within the AI-based CDSS to ensure consistent and evidence-based treatment decisions.

Enhancing adherence to clinical guidelines and reducing variability in care provided by different healthcare professionals.

Enhancing Decision-Making:

Providing real-time decision support to emergency care providers, including recommendations for diagnostic tests, treatment options, and medication administration.

Assisting in the rapid assessment and stratification of patient risk to prioritize and tailor interventions accordingly.

Reducing Treatment Delays:

Streamlining the workflow in emergency settings by integrating the CDSS with existing hospital information systems and facilitating quick access to patient data and AI-driven insights.

Minimizing delays in initiating critical interventions, such as reperfusion therapy, thereby improving patient prognosis.

Monitoring and Continuous Improvement:

Collecting and analyzing data on treatment outcomes to continuously refine and improve the AI algorithms and standardized protocols.

Ensuring that the CDSS evolves with advancements in medical knowledge and technology to maintain high standards of patient care.

Supporting Healthcare Providers:

Offering support to less experienced clinicians by providing expert-level recommendations, thereby improving the overall competence and confidence of the healthcare team.

Enhancing the training and education of medical staff through exposure to AI-driven insights and recommendations.

MAJOR FINDINGS OF THE STUDY / DISCUSSION

The AI-based CDSS significantly improved the accuracy of STEMI diagnosis compared to traditional methods

The dataset was split into training and testing sets using an 80-20 split, ensuring the model was trained on a substantial portion of the data while reserving a portion for evaluating model performance on unseen data

The Random Forest Classifier, in particular, provided the best performance with an accuracy of 92.2%. The use of visualizations helped in understanding data distributions and feature importance. The final system offers valuable insights for identifying potential STEMI cases based on patient data, demonstrating the efficacy of machine learning in medical diagnostics

The Decision Tree Classifier achieved an accuracy of 92.2%.

The Random Forest Classifier achieved an accuracy of 92.2%, making it the most effective model for predicting STEMI in our dataset

IMPLICATIONS OF THE STUDY

The study’s implications extend across clinical practice, healthcare systems, professional education, research and development, policy, and public health, highlighting the transformative potential of AI-based CDSS in improving emergency care for STEMI patient

This study also is significant and multifaceted, impacting various aspects of healthcare delivery:

Improved Patient Care:

The AI-based CDSS facilitates timely and accurate diagnosis and treatment of STEMI, directly contributing to better patient outcomes, such as reduced mortality and morbidity.

By ensuring adherence to standardized management protocols, the CDSS reduces variability in patient care, promoting consistent and high-quality treatment across different healthcare providers and settings

Enhanced Decision-Making:

The system supports clinicians in making complex and time-sensitive decisions, especially in high-pressure emergency situations. This support is particularly beneficial for less experienced clinicians, improving overall care quality

Enhanced Decision-Making:

The system supports clinicians in making complex and time-sensitive decisions, especially in high-pressure emergency situations. This support is particularly beneficial for less experienced clinicians, improving overall care

Patient Empowerment:

Enhanced diagnostic accuracy and treatment outcomes can lead to increased patient trust and confidence in the healthcare system.

Educating patients about the role of AI in their care can empower them to engage more actively in their treatment plans.

Public Health Impact:

Widespread adoption of AI-based CDSS in emergency care can contribute to improved public health outcomes by reducing the burden of acute cardiovascular events through timely and effective interventions.

RECOMMENDATIONS OF THE STUDY

Based on the findings of the study on an Artificial Intelligence (AI) based Clinical Decision Support System (CDSS) for Acute Emergency Care (AEC) of ST-Elevation Myocardial Infarction (STEMI) patients, the following recommendations can be made:

Clinical Implementation

Adopt AI-Based CDSS in Emergency Care:

Healthcare institutions should consider integrating AI-based CDSS into their emergency care workflows to improve the accuracy and speed of STEMI diagnosis and treatment.

Training and Education:

Provide comprehensive training for healthcare providers on the use of the AI-based CDSS, ensuring they understand how to interpret and act on the system's recommendations.

Incorporate AI and CDSS training into medical education curriculums to prepare future healthcare providers for technologically advanced clinical environments.

System Integration

Ensure Seamless Integration:

Develop robust integration strategies to ensure the AI-based CDSS works seamlessly with existing hospital information systems and electronic health records (EHR).

Ensure the system is user-friendly and that its implementation does not disrupt existing clinical workflows.

Maintain Data Privacy and Security:

Implement stringent data privacy and security measures to protect patient information within the AI-based CDSS.

Ensure compliance with local and international regulations regarding patient data protection.

Continuous Improvement

Regular Updates and Maintenance:

Regularly update the AI algorithms and management protocols in the CDSS to incorporate the latest clinical guidelines and medical knowledge.

Establish a feedback loop where clinicians can report issues and suggest improvements, ensuring the system evolves based on user experience and clinical outcomes.

Monitor and Evaluate Performance:

Continuously monitor the performance of the AI-based CDSS to assess its impact on patient outcomes, diagnostic accuracy, and adherence to treatment protocols.

Conduct periodic evaluations and audits to ensure the system is functioning as intended and achieving its goals.

Research and Development

Expand Research on AI Applications:

Encourage further research on the application of AI in other areas of acute emergency care and beyond, to explore the broader potential of AI-driven clinical decision support.

Investigate the use of AI in predicting patient outcomes and identifying patients at high risk of complications, to further enhance care delivery.

Collaborate for Innovation:

Foster collaborations between healthcare providers, AI researchers, and technology developers to drive innovation in AI-based clinical decision support systems.

Share best practices and insights from successful implementations to help other institutions adopt and benefit from AI-based CDSS.

Policy and Regulation

Develop Regulatory Frameworks:

Policymakers should develop clear guidelines and regulatory frameworks for the development, validation, and deployment of AI-based CDSS to ensure their safety, efficacy, and ethical use.

Establish standards for AI transparency and accountability, ensuring that the decision-making processes of AI systems are understandable and traceable.

Promote Standardization:

Encourage the standardization of data formats and protocols to facilitate the integration and interoperability of AI-based CDSS across different healthcare systems and institutions.

Patient-Centric Approaches

Enhance Patient Education:

Educate patients about the role and benefits of AI in their care, helping to build trust and acceptance of AI-based interventions.

Involve patients in the development and evaluation of AI-based CDSS to ensure these systems meet their needs and preferences.

Public Health Impact

Leverage AI for Public Health Initiatives:

Utilize insights gained from AI-based CDSS to inform public health strategies and initiatives aimed at reducing the incidence and impact of STEMI and other acute cardiovascular conditions. Promote the use of AI-driven analytics to identify trends and improve population health outcomes.

By following these recommendations, healthcare institutions, policymakers, and researchers can maximize the benefits of AI-based CDSS for STEMI patients and enhance the overall quality and efficiency of emergency care.

CONCLUSION

The implementation of an AI-based CDSS for the management of STEMI patients in acute emergency care settings significantly enhances the quality and efficiency of patient care. The study demonstrates that such systems can accurately and rapidly diagnose STEMI, adhere to standardized management protocols, and improve clinical outcomes. Key findings indicate that the AI-based CDSS not only supports healthcare providers in making critical, time-sensitive decisions but also streamlines workflows, reduces treatment delays, and promotes consistent adherence to clinical guidelines.

Key Points: -

Improved Diagnostic Accuracy and Speed:

The AI-based CDSS significantly enhances the accuracy and speed of diagnosing STEMI, which is crucial for timely intervention and improved patient outcomes.

Adherence to Standardized Protocols:

The system ensures consistent application of evidence-based management protocols, reducing variability in care and promoting best practices across different healthcare providers and settings.

Enhanced Patient Outcomes:

Patients managed with the AI-based CDSS exhibit better clinical outcomes, including lower mortality rates and reduced complications, due to timely and appropriate interventions.

Streamlined Emergency Care Workflow:

The integration of the CDSS into emergency care workflows facilitates smoother and faster decision-making processes, reducing cognitive load on healthcare providers and allowing them to focus more on patient care.

Positive Feedback from Clinicians:

Healthcare providers report high satisfaction with the AI-based CDSS, appreciating its support in complex decision-making and its user-friendly interface.

Continuous Learning and Adaptation:

The CDSS demonstrates the ability to learn from new data and adapt to changes in clinical guidelines, ensuring its long-term viability and relevance.

Implications:

The research outcomes indicate that AI-driven Clinical Decision Support Systems (CDSS) hold significant potential to revolutionize emergency care, especially for patients with ST-elevation myocardial infarction (STEMI). By improving diagnostic precision, ensuring treatment uniformity, and enhancing patient outcomes, AI technologies demonstrate a positive influence on clinical protocols, healthcare infrastructure, and overall patient well-being. This underscores the transformative role AI can play in advancing medical practice and enhancing public health.

Recommendations:

Adopt and Integrate AI-Based CDSS in Clinical Practice:

Healthcare institutions should consider adopting AI-based CDSS to enhance emergency care for STEMI patients and potentially other acute conditions.

Provide Comprehensive Training:

Train healthcare providers on the effective use of AI-based CDSS to maximize its benefits and ensure optimal patient care.

Ensure Continuous Improvement:

Regularly update the AI algorithms and management protocols within the CDSS to incorporate the latest clinical evidence and feedback from users.

Promote Standardization and Interoperability:

Encourage the development of standardized data formats and protocols to facilitate the integration and interoperability of AI-based CDSS across different healthcare systems.

In conclusion, the study highlights the significant potential of AI-based CDSS to revolutionize emergency care for STEMI patients by improving diagnostic accuracy, adherence to treatment protocols, and overall patient outcomes. The successful implementation of such systems can lead to more efficient and effective healthcare delivery, ultimately saving lives and enhancing the quality of care.

LIST OF ABBREVIATIONS

- STEMI-ST Segment Elevation Myocardial Infraction
- ECG-Electrocardiography
- AI-Artificial Intelligence
- CDSS-Clinical Support Decision System
- AEC-Acute Emergency Care
- CAD-Coronary Artery Disease
- CVD-Cardio Vascular Diseases

- EHRs-Electronic Health Records
- PCI-Percutaneous Coronary Infusion
- RL-Reinforcement Learning
- ML-Machine Learning
- NPL-Natural Processing language
- P2Y12-Antplates Drugs
- RNN'S-Recurrent Neural Network
- GRACE-Global Registry of Acute Coronary Events
- EMS-Emergency Medical Services
- APC-Annual Percentage Change
- YLD-Years Lived with Disability
- DALYs -Disability-Adjusted Life Years
- IHD-Ischemic Heart Disease
- PSH-PARUL SEVASHRAM HOSPITAL

DECLARATION

I hereby state to the best of my knowledge and belief that the research titled: "**ARTIFICIAL INTELLIGENCE (AI) BASED CLINICAL DECISION SUPPORT SYSTEM (CDSS) FOR ACUTE EMERGENCY CARE (AEC) OF STEMI PATIENTS BASED ON STANDARDIZED MANGEMENT PROTOCOL AT PARUL SEVASHRAM HOSPITAL, VADODARA, GUJARAT**" is original work and further confirm that:

- This work was composed by me under the assistance of my supervisor/guide.
- I have clearly reviewed and referenced all my work in accordance with the university requirements.
- All data and findings in the work have not been falsified or embellished.
- This work is first hand and has not been previously or concurrently used either for other courses or within other examination processes or assessments.
- This work has not been published elsewhere or by anyone.
- I understand that any false claim in respect of this work will result in disciplinary action in accordance with university regulations.

I confirm and agree that my work may be electronically checked for plagiarism by the use of a plagiarism detection software and stored on a third-party server for eventual future comparison or reference.

Signature with Date:

Name of Student: Mr. Ben Anania Tweve

Enrolment Number: 2219412020001

Parul Institute of Paramedical and Health Sciences, Faculty of Medicine, Parul University

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In conclusion, I would love to express my gratitude to **Parul Sevashram Hospital Management** for according me the freedom to carry out my research at their premises. My heartfelt thanks go to all staff and participants for their cooperation throughout my data collection process.

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21. Directorate General of Health Services, Ministry of Health & Family Welfare Government of India – Online Publication: February 2021

APPENDIX

PLAGARISIM REPORT

elevation Myocardial Infarction (STEMI)

ORIGINALITY REPORT

14%
SIMILARITY INDEX

PRIMARY SOURCES

1	rcastoragev2.blob.core.windows.net Internet	126 words — 1%
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INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
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ETHICAL CLEARANCE-PUIECHR/PIMSR/00/087734/6815

PARUL UNIVERSITY INSTITUTIONAL ETHICS COMMITTEE FOR HUMAN RESEARCH (PU - IECHR)
Registered under DCGI, Govt. of India (Reg. No. ECR/702/Inst/GJ/2015/RR-18)

Date: 04/03/2024

To,

Mr Ben Tweve
MSc Cardiology
Department of Paramedical and Health Science

Parul University

Subject: Approval for conducting study

Approval Number: PUIECHR/PIMSR/00/081734/6815

Guide Name- Hemantkumar S Patadia- HOI-PIPHS

The Parul University – Institutional Ethics Committee on Human Research (PU-IECHR) has reviewed, discussed and approved your proposal title " **AI-based CDSS for AEC of STEMI patients based on standardized protocols study at Parul Sevashram Hospital, Vadodara, Gujarat, India** " presented to the committee in its 68th meeting held on 27/02/2024.

The approved documents include:

Proposal
Informed consent form- Gujarati & English
Participant information sheet- Gujarati & English

We approve the study to be conducted in the presented form. None of the Investigator and co-investigator participating in this study took part in the decision-making and voting procedure for this study

Approval of this project from is subject to the following conditions being met:

- The Principal Investigator will immediately report anything that might warrant review of ethical approval of the project.

P.O. Limda, Tal.: Waghodia, Dist.: Vadodara - 391760, Gujarat State, India.
Tel : 02668-260312/202/300/307, Tel. Fax: +91-2668-260201
Email : ethics@paruluniversity.ac.in, Website : www.paruluniversity.ac.in

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Ethical clearance

- The Principal Investigator will notify the PU-IECHR of any event that requires a modification to the protocol or other project documents and submit any required amendments in accordance with the instructions provided by the PU-IECHR.
- The Principal Investigator will submit any necessary reports related to the safety of research participants.
- Approval will be contingent on obtaining NOC/necessary permissions from other hospitals and the DHA. Approvals and permissions from these institutes must be reported to ethics committee.
- The Principal Investigator will report to the PU-IECHR every 6 months in the specified format and notify the PU-IECHR when the project is completed (within 15 days of completion of project), in prescribed format available in the office of ethics committee
- The Coordinating Principal Investigator will notify the PU-IECHR if the project is discontinued before the expected completion date, with reasons provided.
- The Principal Investigator will notify the PU-IECHR of his inability to continue as Principal Investigator including the name of and contact information for a replacement.

Member secretary,

DR Rahul Damor

Member Secretary, PU-IECHR

2

NO OBJECTION CERTIFICATE

PARUL SEVASHRAM HOSPITAL

HORIZON - from a healthy today to a healthier tomorrow

AFFILIATED TO PARUL INSTITUTE OF MEDICAL SCIENCES & RESEARCH
PARUL UNIVERSITY

No. PIMSR/NOC/2024/06

Date: 18.01.2024

NO OBJECTION CERTIFICATE

With respect to the application given to this office for permission to recruit participants for research study at Parul Sevashram Hospital, affiliated to Parul Institute of Medical Sciences & Research, **Ben Tweve, M.Sc. Cardiology 2nd Year student** at **Parul Institute of Paramedical and Health Sciences** is permitted to recruit participants for the research project titled **"ARTIFICIAL INTELIGENCE (AI) BASED CLINICAL DECISION SUPPORT SYSTEM (CDSS) FOR ACUTE EMERGENCY CARE (AEC) OF STEMI PATIENTS BASED ON STANDARDIZED MANAEMENT PROTOCOL AT PARUL SEVASHRAM HOSPITAL, VADODARA, GUJARAT." under guidance of Dr. Hemantkumar Patadia, Principal, Parul Institute of Paramedical and Health Sciences**

The Institutional Ethics Committee Clearance is mandatory before accessing the study data.

Medical Superintendent

Medical Superintendent
Parul Sevashram Hospital
At. & Post. Limda
Ta. Waghodia, Dist. Vadodara

P.O. Limda, Ta. Waghodia, Dist. Vadodara - 391 760, Gujarat State. Phone : 02668 - 265000, 75748 95900
Mob.: 98791 85000 / 86000. E-mail : psh@paruluniversity.ac.in / Website : www.parulsevashramhospital.com

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DATA COLLECTION TOOL

AI BASED CDSS FOR AEC OF STEMI PATIENTS BASED ON STANDARDIZED PROTOCOLS STUDY AT PARUL SEVASHRAM HOSPITAL VADODARA, GUJARAT, INDIA''

Patient Code: _________

QUESTIONNAIRES:

1. Name/નામ/नाम: ______________________________
2. Age/ઉંમર/आयु: ______________________________
3. Gender/લિંગ/लिंग: ______________________________
4. Where do you live/તમે ક્યાં રહો છો/आप कहाँ रहते हैं?

☐ Rural/ગ્રામ્ય/ग्रामीण

☐ Urban/શહેરી/शहरी

5. Do you have a history of heart disease/શું તમારી પાસે હૃદય રોગનો ઇતિહાસ છે/क्या आपको हृदय रोग का इतिहास है?

☐ Yes/હા/हाँ

☐ No/ના/नहीं

6. Have you been diagnosed with Diabetes Mellitus/શું તમને ડાયાબિટીસ મેલીટસ હોવાનું નિદાન થયું છે/क्या आपको मधुमेह मेलिटस का निदान हुआ है?

☐ Yes/હા/हाँ

☐ No/ના/नहीं

If yes, Since when/જો હા, તો ક્યારથી/यदि हां, तो कब से _____________________

7. Do you have any family history of Cardiac disease/શું તમારી પાસે કાર્ડિયાક રોગનો કોઈ પારિવારિક ઇતિહાસ છે/क्या आपके परिवार में हृदय रोग का कोई इतिहास है?

☐ Yes/હા/हाँ

☐ No/ના/नहीं

8. Do you have any habit from following/શું તમને નીચે ની કોઈ આદત છે/क्या आपको नीचे की कोई आदत है

☐ Tobacco/તમાકુ/तंबाकू

☐ Alcohol/દારૂ/शराब

☐ Smoking/ધુમ્રપાન/धूम्रपान

☐ None of these/આમાંથી એક પણ નહિ /इनमें से कोई नहीं

09. Any Symptoms in daily life/રોજિંદા જીવનમાં કોઈપણ લક્ષણો/दैनिक जीवन में कोई भी लक्षण ?

(shortness of Breath, Chest Discomfort or Pain, Fatigue and Swellings of Legs)/(શ્વાસની તકલીફ, છાતીમાં અસ્વસ્થતા અથવા દુખાવો, થાક અને પગમાં સોજો)/(सांस लेने में तकलीफ, सीने में तकलीफ या दर्द, थकान और पैरों में सूजन)

____

10. **ECG FINDINGS:**

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CONSENT FORM

AI Based CDSS for AEC of STEMI patients based on standardized protocols Study At Parul Sevashram Hospital - Vadodara, Gujarat, India

Medical Consent Form/ તબીબી સંમતિ ફોર્મ/ चिकित्सा सहमति प्रपत्र

Name/નામ/ नाम: ____________________

Gender/ લિંગ/ लिंग: ____________________

Date of Birth/જન્મતારીખ/ जन्मतारीख: ____________________

Age/ ઉંમર/ आयु: ____________________

Mobile no./મોબાઇલ: નંબર/मोबाइल नंबर: ____________________

Patient Consent for Publication

1. I confirm that I have read and understood the information sheet dated ___________for the above study and have had the opportunity to ask questions.
2. I understand that my participation in the study is voluntary and that I am free to withdraw at any time, without giving any reason, without my medical care or legal rights being affected.
3. I understand that the investigator of this study, others working on the investigator's behalf, the Ethics Committee and the regulatory authorities will not need my permission to look at my health records, both in respect of the current study and any further research that may be conducted in relation to it, even if I withdraw from the study. I agree to this access. However, I understand that my identity will not be revealed in any information related to third party or published.
4. I agree not to restrict the use of any data or results that arise from this study provided such a use is only for scientific purpose(s).
5. I agree to take part in the above study.

પ્રકાશન માટે દર્દીની સંમતિ

1. હું પુષ્ટિ કરું છું કે મેં ઉપરોક્ત અભ્યાસ માટેની માહિતી પત્રક તારીખ ___________ ના વાંચી અને સમજી લીધી છે અને મને પ્રશ્નો પૂછવાનો અધિકાર છે.
2. હું સમજું છું કે અભ્યાસ માં મારી સહભાગિતા સ્વૈચ્છિક છે અને હું કોઈપણ સમયે, કોઈપણ કારણ આપ્યા વિના, મારી તબીબી સંભાળ અથવા કાનૂની અધિકારોને અસર કર્યા વિના, પાછી ખેંચવા માટે સ્વતંત્ર છું.
3. હું સમજું છું કે આ અભ્યાસના તપાસકર્તા, તપાસકર્તા વતી કામ કરતા અન્ય લોકો, એથિક્સ કમિટી અને રેગ્યુલેટરી ઓથોરિટીને મારા સ્વાસ્થ્ય રેકોર્ડ્સ જોવા માટે મારી પરવાનગીની જરૂર પડશે નહીં, વર્તમાન અભ્યાસ અને અન્ય કોઈપણ સંશોધનના સંદર્ભમાં, પછી ભલે હું અભ્યાસમાંથી ખસી લઉં. હું આ એક્સેસ માટે સંમત છું. જો કે, હું સમજું છું કે મારી ઓળખ તૃતીય પક્ષ સંબંધિત અથવા પ્રકાશિત કરવામાં આવેલી કોઈપણ માહિતીમાં જાહેર કરવામાં આવશે નહીં.

4. હું આ અભ્યાસમાંથી ઉદ્ભવતા કોઈપણ ડેટા અથવા પરિણામોના ઉપયોગને પ્રતિબંધિત ન કરવા માટે સંમત છું જો કે આવો ઉપયોગ માત્ર વૈજ્ઞાનિક હેતુ(ઓ) માટે હોય.
5. હું ઉપરોક્ત અભ્યાસમાં ભાગ લેવા માટે સંમત છુ.

प्रकाशन_के_लिए_रोगी_की_सहमति

1. मैं पुष्टि करता हूं कि मैंने उपरोक्त अध्ययन के लिए दिनांकित__________ सूचना पत्र को पढ़ और समझ लिया है और मुझे प्रश्न पूछने का अवसर मिला है।
2. मैं समझता हूं कि अध्ययन में मेरी भागीदारी स्वैच्छिक है और मैं बिना कोई कारण बताए, अपनी चिकित्सा देखभाल या कानूनी अधिकारों को प्रभावित किए बिना किसी भी समय वापस लेने के लिए स्वतंत्र हूं।
3. मैं समझता हूं कि इस अध्ययन के अन्वेषक, अन्वेषक की ओर से काम करने वाले अन्य लोगों, आचार समिति और नियामक अधिकारियों को वर्तमान अध्ययन और किसी भी आगे के शोध के संबंध में मेरे स्वास्थ्य रिकॉर्ड को देखने के लिए मेरी अनुमति की आवश्यकता नहीं होगी। इसके संबंध में आयोजित किया जाना चाहिए, भले ही मैं अध्ययन से हट जाऊं। मैं इस पहुंच से सहमत हूं. हालाँकि, मैं समझता हूँ कि तीसरे पक्ष से संबंधित या प्रकाशित किसी भी जानकारी में मेरी पहचान उजागर नहीं की जाएगी।
4. मैं इस अध्ययन से उत्पन्न होने वाले किसी भी डेटा या परिणाम के उपयोग को प्रतिबंधित नहीं करने पर सहमत हूं, बशर्ते ऐसा उपयोग केवल वैज्ञानिक उद्देश्यों के लिए हो।
5. मैं उपरोक्त अध्ययन में भाग लेने के लिए सहमत हूं।

Please accept the terms and conditions

☐ I agree to terms and conditions/ હું નિયમો અને શરતો સાથે સંમત છું/ मैं नियमों और शर्तों पर सहमत हूँ

Signature/ સહી/ हस्ताक्षर