Predicting In-Hospital Cardiac Arrest Using Machine Learning Models: A Scoping Review Protocol

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Abstract

Background: In-hospital cardiac arrest (IHCA) remains a public health conundrum with high morbidity and mortality rates. While early identification of high-risk patients could enable preventive interventions and improve survival, evidence on the effectiveness of current prediction methods remains inconclusive. Limited research exists on patients' pre-arrest pathophysiological status, predictive, and prognostic factors of IHCA, highlighting the need for a comprehensive synthesis of predictive methodologies.

Objective: This scoping review aims to synthesize and critically evaluate the quality and quantity of clinical features and machine learning (ML) models for predicting IHCA. The review will evaluate temporal characteristics, predictive and prognostic values of pre-arrest clinical features, and model performance metrics.

Methods: Following PRISMA-ScR guidelines, peer-reviewed studies from April 2009 to April 2024 using ML to predict IHCA will be included. Data sources include PubMed, Web of Science, IEEE, and Embase. Two reviewers will independently screen, extract, and assess the quality of included studies. Data will be synthesized using descriptive statistics and narrative summaries.

Results: The review will provide insights into common clinical predictors, data quantity and quality, and ML model metrics for IHCA prediction. Findings will identify gaps and offer practical recommendations for standardizing clinical features in ML modeling.

Conclusions: This study will contribute to advancing ML applications for IHCA prediction by addressing data challenges and promoting standardization to improve clinical decision-making process.

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***Keywords*:**; Machine Learning; Electronic Health Records; Artificial Intelligence; Cardiac Arrest; Predictive Value of Tests; Resuscitation.

Introduction

In-hospital cardiac arrest (IHCA), defined as the absence of a pulse and need for defibrillator shocks and/or chest compressions in a patient admitted to an inpatient bed—remains a significant public health challenge in the United States (U.S.), with approximately 292,000 cases occurring annually [1-3]. Mortality rates for ICHA are 80% for patients with non-shockable rhythms and 55% for those with shockable rhythms, and 1-year survival after IHCA is only 13% [2,4,5]. Early identification of high-risk patients could facilitate the implementation of preventive interventions to reduce mortality and potentially improve 1-year survival rates. However, evidence regarding the effectiveness of current prediction methods (e.g., scoring systems) and established practices for preventing IHCA remains inconclusive [6,7]. Moreover, despite documented differences between IHCA and out-of-hospital cardiac arrest (OHCA) [8], treatment guidelines for the two types remain the same. IHCA has been less studied compared to OHCA, with a recent study reporting 61 published randomized controlled trials (RCTs) involving OHCA, compared to only 15 for IHCA (2015–2022) [9]. Most IHCA studies have focused on patient outcomes during or post-resuscitation, with limited research into the complex pre-arrest pathophysiological changes. Recent evidence, however, has challenged traditional assumptions about the causes of

IHCA (e.g., hypoxia). Conditions such as sepsis/infection and heart failure, which lead to circulatory and respiratory collapse, have been identified as significant contributors which enhance our understanding of IHCA causes [10]. A deeper understanding of the complex pathophysiological changes and factors contributing to IHCA would enable the development of more accurate tools, early initiation of preventive measures, and more effective treatment strategies.

Gathering the evidence necessary to develop predictive models for IHCA has been challenging due to the lack of publicly available registries [11] containing pre-arrest longitudinal data, such as physiological measures. Electronic health records (EHRs) from hospitals and medical centers represent another potential source of data. However, several challenges have hindered the optimal use of these records for clinical research. Chief among these challenges are missing data and concerns about data accuracy. For example, vital signs recorded in the EHR are frequently used to develop clinical tools (e.g., early warning scores) for predicting IHCA. Yet, these measures depend on bedside clinicians' documentation, and studies have raised concerns about their accuracy and completeness [12,13].

Nevertheless, EHRs are an important source of big data for developing machine learning (ML) models to predict adverse health events. ML, a branch of artificial intelligence (AI), involves the development of algorithms that enable computer systems to learn from data, recognize patterns, and make predictions based on those patterns [14]. ML models can handle large, diverse data sets and uncover complex nonlinear relationships between features (i.e., input data) to predict outcomes. In contrast, conventional statistical methods are limited to discovering linear relationships between variables, such as patient characteristics and outcomes, however; the superiority of machine learning models to statistical models is still controversial [15-19]. The EHR comprises a vast set of time-series data, which enhances the accuracy and performance of ML-based decision-making systems [19]. However, because the accuracy of ML predictive models depends heavily on unbiased and diverse training data, investigators developing these models must have a comprehensive understanding of the known causes of the event or condition they are predicting, the characteristics of the targeted population, and confounding variables (e.g., sex differences) as well as access to a large, accurate set of time-series data.

Despite the clinical and organizational challenges of studying IHCA, such as missing or inaccurate data, the number of studies using ML models to predict IHCA has been increasing in recent years. However, there is limited IHCA review literature (e.g., systematic review) examining the prognostic and predictive pre-arrest factors in predicting IHCA. Only one systematic review study[20] was found that evaluated the performance of ML models in predicting IHCA by comparing them with the clinical predictive tool (i.e., modified early warning score [MEWS]), and it concluded that AI-ML models were superior. The quality and quantity of input data were not examined in this study; instead, the emphasis was on evaluating the performance of the ML models. Furthermore, several selected studies included composite outcomes (e.g., combination of death, cardiac arrest, unit transfer) and did not provide separate ML metrics specifically for predicting IHCA. This review was conducted in 2020 and did not include literature published in the past 4 years.

Additionally, the term “in-hospital cardiac arrest” was not used as one of the search keys for finding the ML articles.

Given the increasing use of ML models in predicting IHCA, the clinical, and organizational challenges associated with this emerging field, it is imperative to conduct a scoping review to identify gaps in current ML studies. These challenges include issues like missing data and the complexities of working with EHRs in clinical settings. To the best of authors’ knowledge, no existing scoping review has synthesized and critically evaluated the quality and quantity of selected features used in ML models for predicting IHCA. This includes aspects such as patient characteristics, the temporal characteristics of collected data (e.g., time of IHCA), the predictive value of pre-arrest clinical features, and the performance metrics of ML models. Findings from this scoping review will not only highlight these gaps but also provide practical recommendations for standardized reporting of clinical features as integral components of ML modeling. Such standardization is crucial for improving the accuracy and applicability of ML models in clinical decision-making process to improve the quality of patient care.

Methods

A scoping review will be conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The protocol has been developed using checklists in the PRISMA extension for scoping reviews (PRISMA-ScR) [21].

Review question

Our review questions are:
1. What are the quality and quantity characteristics of clinical data used to construct ML models?
2. What are the common clinical predictors shared among multiple ML models?
3. What are the strongest predictive metrics for occurrence of IHCA?

Ethical Consideration

This review will not involve direct contact with human subjects. All clinical data (i.e., laboratory results and vital signs) used in ML model construction will be presented as aggregated and deidentified data from previously published studies. The Protocol of this scoping review has been registered in the Open Science Framework (OSF) available at https://osf.io/kmnf5 after conducting a peer-review process to select relevant articles on IHCA and ML techniques.

Eligibility Criteria

The focus of this protocol is to synthesize the clinical features used to construct ML models and evaluate the performance of these models in predicting IHCA.

Inclusion and exclusion criteria

Articles: We will include only peer-reviewed, English-language studies published between April 2009 and April 2024, which utilized ML algorithms to predict IHCA. We will exclude the following types of articles:

a. Reviews (e.g., systematic reviews and meta-analyses)

b. Pre-prints, conference proceedings, theses, dissertations
c. Studies published in foreign languages, abstract-only studies, opinions, letters to the editor, commentaries, short communications, and patents.

Patient Population: Only studies involving adults aged ≥18 years or older who experienced IHCA will be included. There will be no restriction based on sex, gender, geographic location, race, or types of machine learning techniques used. We will use the Utstein Resuscitation Registry definition of IHCA [1], which refers to the delivery of defibrillator shocks or chest compressions to a patient admitted to an in-patient. Studies that do not adhere to this definition or that did not collect data from hospitals/medical centers will be excluded. Additionally, studies that include cases of death or sudden death without resuscitation, out-of-hospital cardiac arrest, or animal studies will be excluded.

Study Outcomes and ML Metrics: Some studies list composite outcomes, including IHCA, admission to intensive care units, patient deterioration. We will include only those articles that provide separate ML metrics specifically for predicting IHCA, regardless of other composite outcomes.

Information sources

Four reputable databases were searched, including PubMed (biomedical research), Web of Science (a global citation database in the sciences, arts, and humanities), IEEE (for technology and engineering research), and Embase (medical research). The following two sets of search terms including “in-hospital cardiac arrest”, “machine learning” were entered into the databases connected with “AND” after trials of selecting different text words.

Search strategy

An interprofessional informationist team member worked with disciplinary faculty and created the base search to refine key concepts. The informationist completed a pilot search in PubMed which a team member screened to determine retrieval accuracy for key articles on in-hospital cardiac arrest and machine learning. For example, we initially selected the following search terms and key words using Medical Subject Headings (MESH) database:

(“In-hospital cardiac arrest” [Text Word] OR “In-hospital cardiac arrest” [tiab] OR “cardiopulmonary resuscitation” [Text Word] OR “heart arrest” [Text Word] OR “sudden cardiac death” [Text Word] OR asystole [Text Word] OR heart arrest [MeSH] OR asystole [MeSH] OR cardiopulmonary arrest [MeSH] OR arrest, cardiopulmonary [MeSH]) **AND** (“Artificial intelligence” [Text Word] OR “artificial intelligence” [tiab] OR Artificial intelligence [MeSH] OR Intelligence, Artificial [MeSH] OR Computational Intelligence [MeSH] OR Intelligence, Computational [MeSH] OR Machine Intelligence [MeSH] OR Machine Learning [MeSH] OR Deep Learning [MeSH] OR Supervised Machine Learning + [MeSH] OR Unsupervised Machine Learning [MeSH]) 2009-2024

Each trial was conducted by choosing carefully selected keywords involving Boolean operators and MeSH options along with other text words using with or without assigned year (2009-2024) which produced a set number of articles. These articles were reviewed by a team member with expertise in IHCA and familiarity with machine learning techniques. Then, a discussion was initiated between the informationist and the team member to improve search terms for targeted peer-reviewed articles in PubMed. This process was iterated for seven times producing a range of published articles from 95 to 2,004. Based upon the search sensitivity, revisions were completed on the search query which was then translated from PubMed into three additional databases: Web of Science, Embase, and IEEE for hand searching. A second research librarian will conduct a full Peer Review of Electronic Search Strategy (PRESS) review of the search and will recommend revisions.

The phrase “in-hospital cardiac arrest” is not part of keywords in the MESH database yet. This can be explained partially by the fact that IHCA is emerging as a new field of study. Using the keyword of “in-hospital cardiac arrest” in PubMed resulted in 1,819 while using "out-of-hospital cardiac arrest" keyword resulted in 11,784 publications (search performed on 11/05/2024). Nevertheless, the number of IHCA publications has been increasing over the past 10 years.

Screening

All search results will be downloaded and exported into Rayyan for de-duplication. Automated tools in Rayyan will be used to identify and remove duplicates. Once duplicates are removed, the titles and abstracts will be screened according to the exclusion criteria, and the articles that do not meet the criteria will be excluded. The full text of the remaining articles will be then reviewed to determine eligibility, with reasons for exclusion recorded and reported in the final scoping review. Two reviewers will independently conduct the screening process independently utilizing Rayyan applications. Any disagreement between the reviewers will be resolved through discussion, with input from experts in resuscitation and data sciences. The results of the search (i.e., included articles) will be presented in a PRISMA flow diagram.

Data extraction and main data elements

Our reviews aims and questions will guide types of data elements for extraction. The targeted data element will be identified and will be extracted from the eligible full texts of the articles by two team members who will record them as variables in a developed template using Microsoft Excel. We will have several sheets within an excel file to complete data charting (e.g., demographics, biomarkers). The excel file can be considered as our tool and will be revised as necessary during the extraction phase. The extracted data will be reviewed by the third member for accuracy. To resolve any conflict, a discussion among all these team members will be conducted to reach consensus. A list of data element for future extraction is presented in Figure 1.

Data analyses and presentation

Descriptive statistics including numbers, percentage, means, and standard deviations will be reported to quantify the selected variables and a comprehensive narrative will provide detailed synthesis of variables across the articles (e.g., age). Tables will be used to present key variables such as the names of laboratory tests included in the models and medical histories of participants (e.g., diagnoses). The number and type of all ML models (i.e., traditional versus deep neural network) will be presented in a graph. The best metrics of ML models will be presented in a table including the area under the curve (AUC), area under the receiver operating characteristics (ROC), sensitivity, specificity, negative predictive value, positive predictive value, accuracy, precision, and F1 score (Figure 2).

Results

Our research for this review started in April 2024. The data extraction and analyses which would be completed by the end of December 2024. We will present our work in national meetings relevant to the topic of cardiac arrest/resuscitation topic and submit our findings to a peer-reviewed journal to share knowledge and increase the awareness about the state-of-the art in predicting IHCA by using artificial intelligence.

The results will address each of our questions by providing specific findings presented as descriptive statistics and detailed narrative summary. We created a comprehensive search strategy to identify articles that used ML models to predict IHCA. Our consistent work will be presented as a scoping review which contains detailed and aggregated information summarizing data by using tables and graphs. Please see Figure 3 for project milestones and associated timelines.

Discussion

We will conduct a comprehensive evaluation of the clinical features extracted from Electronic Health Records (EHR) for each phase of machine learning (ML) model development, including training, validation, and testing. This evaluation will focus on assessing population diversity, such as age, sex, race/ethnicity, and comorbidities, to ensure inclusivity and representation in model development. Recognizing that EHR data often contains time-series information, we will thoroughly analyze the temporal characteristics of clinical features, particularly in relation to the timing of in-hospital cardiac arrest (IHCA) onset. This includes exploring patterns, trends, and critical time points that could enhance the predictive power of ML models.

Furthermore, we will identify and discuss the significance of commonly reported predictors across studies, such as vital signs, lab results, and comorbid conditions, and critically evaluate their clinical implications. This will provide insight into the relevance of these predictors in the context of IHCA and their potential utility in real-world clinical settings.

Special emphasis will be placed on enhancing the interpretability of ML models, addressing the "black box" challenge often associated with these approaches. Techniques such as feature importance analysis, visualization of decision pathways, and integration of domain knowledge will be explored to improve the transparency and usability of ML predictions. The discussion will also cover the metrics and methodologies for optimizing model performance, including sensitivity, specificity, precision, recall, and calibration, with a focus on their implications for clinical decision-making and patient outcomes. Through this synthesis, we aim to support the standardization of reported clinical features and methodologies in the development of predictive ML models for IHCA. This standardization will facilitate comparability across studies, enhance reproducibility, and ultimately contribute to the broader adoption of ML tools in clinical practice for early detection and prevention of IHCA.

Strengths and Limitations

This study will have several strengths and limitations. Among its strengths, it will provide a comprehensive analysis of clinical features extracted from EHR data, considering population diversity and temporal dynamics. This ensures the findings are inclusive and applicable across varied patient populations. The focus on temporal characteristics is another strength, as it addresses the critical aspect of timing in predicting IHCA, enabling better anticipation of adverse events. Additionally, the study places significant emphasis on interpretability, tackling the "black box" nature of ML models and ensuring results are transparent and usable by clinicians, fostering trust and adoption in healthcare. Furthermore, the synthesis of predictors and features across studies will support standardization in reporting practices, enhancing reproducibility and comparability in ML model development. The emphasis on clinical relevance will bridge the gap between technical advancements and practical implementation, while considerations of population diversity promote equity and reduce biases in predictive models.

However, the study will also face certain limitations. The quality, completeness, and standardization of EHR data, which can vary across institutions, may impact the analysis and model performance. Despite efforts to include diverse populations, biases in available datasets could limit the generalizability of findings, especially for underrepresented groups. While interpretability is emphasized, some ML models may remain opaque due to their inherent complexity. Additionally, a scoping review has inherent limitations that stem from its methodology and objectives, which focus on mapping existing literature rather than providing definitive answers to specific research questions. One primary limitation is the lack of depth in analysis, as scoping reviews typically do not involve a critical appraisal of the quality of included studies. This means that studies with varying levels of rigor may be included, potentially affecting the reliability of the findings. Additionally, the heterogeneity of evidence, including diverse study designs, populations, and outcomes, can make it challenging to synthesize findings into cohesive conclusions. Unlike systematic reviews or meta-analyses, scoping reviews do not perform formal meta-analyses or provide pooled effect estimates, limiting their ability to quantify relationships or provide definitive conclusions. The broad scope of the scoping review may also introduce selection bias, as the inclusion of studies depends on the search strategy, availability of data, and reviewer judgment. Moreover, this scoping review will rely heavily on published and accessible literature, potentially overlooking unpublished studies, grey literature, or ongoing research, leading to the publication bias. Despite these challenges, the study provides valuable insights and a balanced contribution to the development and evaluation of ML models for predicting IHCA.

Conclusion

Our scoping review will add to the body of IHCA literature by synthesizing different aspects of machine learning studies to predict IHCA. This will be our first step to comprehend the complexity of machine learning studies and promote realistic options for the clinical decision-making process.

Conflict of Interest

None declared.

Figure 1. Name of variables that will be extracted from selected article

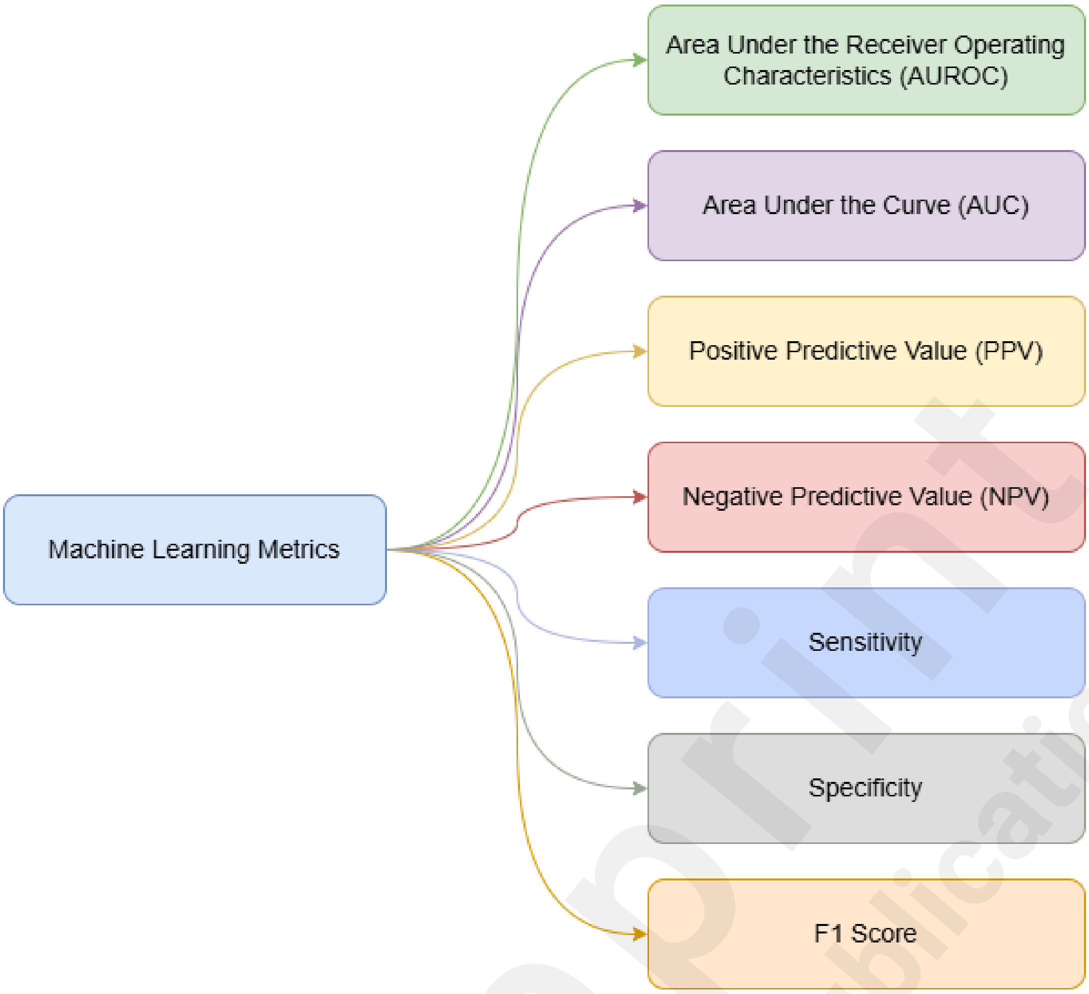

Figure 2. Metrics of machine learning models

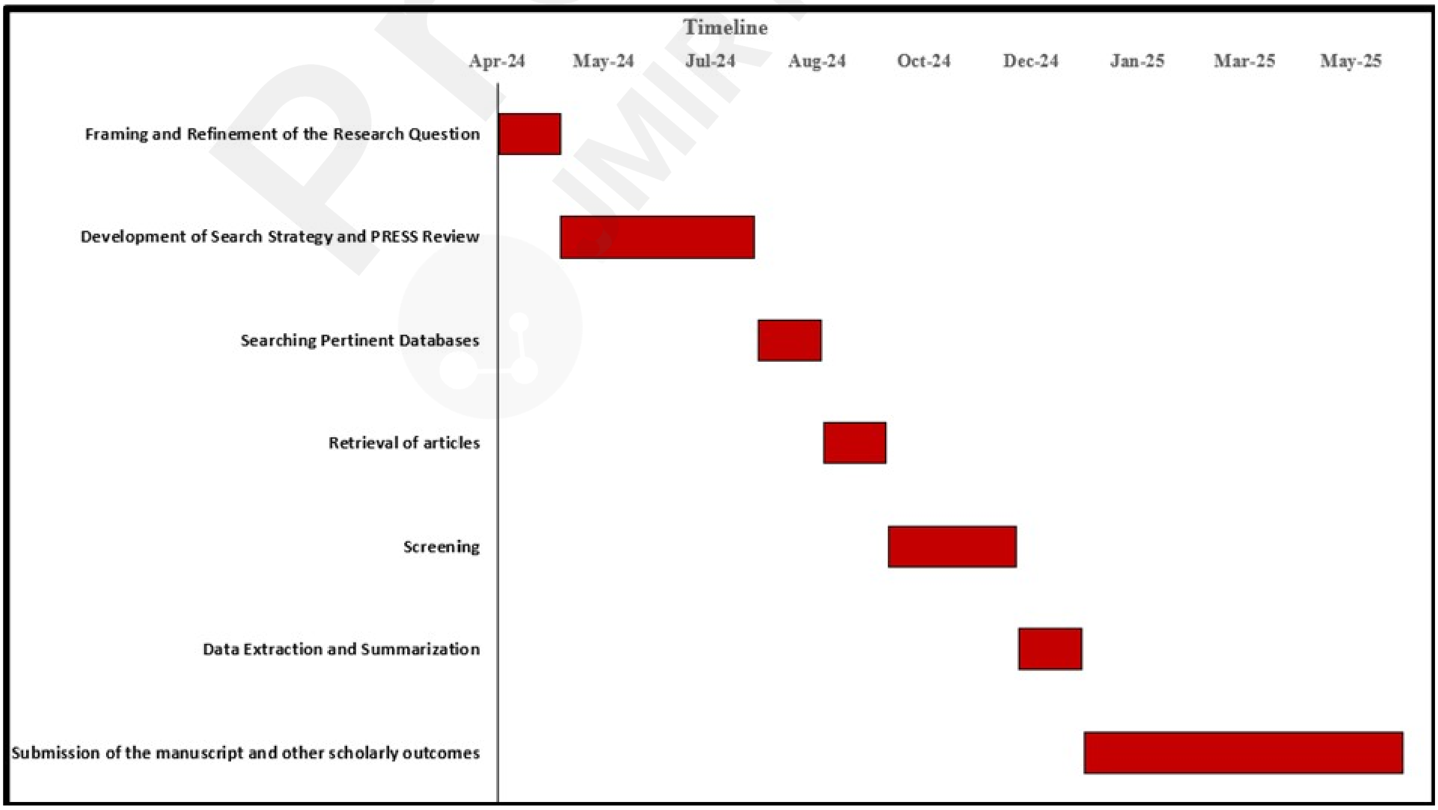

Figure 3. Gantt graph showing the project milestones and associated timelines

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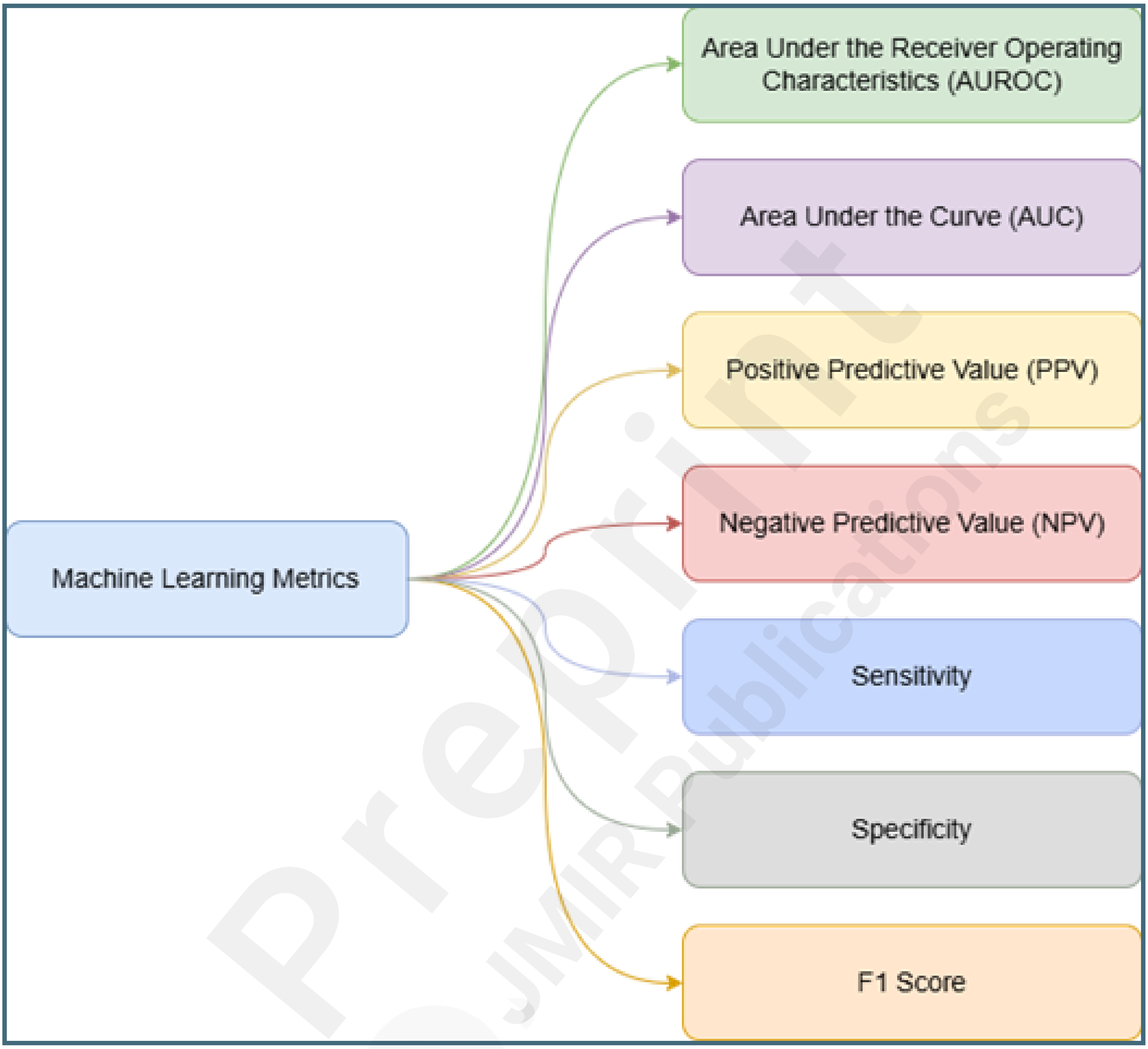
Supplementary Files

Figures

Name of variables that will be extracted from selected article.

Metrics of machine learning models.



Gantt graph showing the project milestones and associated timelines.