Knowledge Graph-Enhanced Artificial Intelligence for Intelligent Clinical Decision Support

Md Mehedi Hassan Melon[1], Mazharul Islam[2], Md Sumon Rana[3], Md Fazlay Rabby[4], Md Mahidur Rahman[5], Nayem Miah[6], Kallol Chakraborty Shekhor[7], Md Azharul Islam[8], MD Mizanur Rahman[9]

[1] Electrical And Automation Engineering ,Nanjing Tech University , China
[2] Graduate School of Management Information Systems, Dong-A University, Busan, Korea
[3] Department of Zoology, University of Dhaka, Dhaka, Bangladesh
[4] Masters of Business Administration, Sejong university
[5] Electrical Engineering And Automation, Nanjing Tech University
[6] Department of Anthropology, Comilla University, Cumilla, Bangladesh
[7] Assistant Manager-Software and Web, Kazal Brothers Limited , Dhaka , Bangladesh
[8] B.sc in Computer Science and Engineering (CSE),Royal University Dhaka,Bangladesh
[9] Information Technology Department, Padma Islami Life Insurance Limited, Dhaka, Bangladesh

Abstract

The adoption of Artificial Intelligence (AI) in healthcare continues to grow in order to enhance clinical decision-making and patient outcomes. Most of the traditional machine learning models that are applied in clinical prediction activities are extensively based on statistical trends and are not necessarily interpretable or have medical contextual information. As a way of overcoming these shortcomings, this research paper suggests a Knowledge Graph-Enhanced Artificial Intelligence model of intelligent clinical decision support with the use of ICU patient data. The study uses the MIMIC3c Aggregated Dataset which is based on the MIMIC-III Clinical Database and has aggregated hospital interaction data in intensive care unit hospitalizations. The data has demographic information of patients, details of admission, clinical diagnosis, and daily interaction data, including laboratory tests, medications, imaging reports, caregivers, and clinical orders. These interaction characteristics give information about the medical care severity and the severity of patient condition. The dataset will be preprocessed in this research to process missing values, as well as, encode categorical variables and normalize numbers. This is followed by the construction of a knowledge graph representation to represent the relationship among major clinical entities, e.g. patients, diagnoses, types of admission, and treatment interactions.

Keywords: Knowledge Graph, Artificial intelligence in healthcare, Clinical Decision Support System, ICU Mortality Prediction, Machine Learning and Healthcare Data Analytics

I. Introduction

A. Background of the Study

The fast development of digital technologies has had a great impact on the healthcare sector, causing the creation of huge amounts of medical data by hospitals, laboratories, and clinical monitoring systems. The use of electronic health records (EHRs) is becoming a common practice in modern healthcare facilities to maintain a complete record of patient data, such as demographic, diagnosis, treatment, medication history, and clinical outcome information. Such massive data sets offer good prospects to both researchers and medical practitioners to process patient data and derive meaningful information after using modern computation models. Machine learning and Artificial Intelligence (AI) have become potent tools to analyze healthcare data and allow forming predictive models that can be used to assist clinical decision-making and achieve better patient outcomes [1]. The past few years have seen a great application of predictive analytics in healthcare to perform activities like disease diagnosis, risk assessment, patient monitoring and treatment recommendation. The different machine learning models that have been effectively applied to find patterns in healthcare data and predict clinical outcomes include logistic regression, decision trees, random forests, support vectors machines, and neural networks [2]. Although they are generally performing well, most of these models are black-box and have low interpretability, as well as they are not able to discover intricate relationships between medical entities. The absence of transparency in predictive models can decrease the trust of healthcare practitioners in the implementation of AI-based systems in critical healthcare settings (especially in intensive care units (ICUs)). In order to overcome these shortcomings, knowledge graphs have been proposed as an interesting way of modeling structured medical knowledge [3]. A knowledge graph is a structure of data made up of interrelatives and links which allows the illustration of multifaceted interactions between patients, diseases, drugs, and clinical workflows. Knowledge graphs can bring about contextual insight and enhance the explicability of predictive results when combined with artificial intelligence models [4]. This integration improves the ability of clinical decision support systems to integrate data-driven analytics with formal medical knowledge, which ultimately leads to a higher degree of reliable, interpretable and intelligent healthcare solutions.

II. Literature Review

A. Machine Learning and Artificial Intelligence in Health Care Analytics

Machine learning and Artificial Intelligence (AI) have been important in revolutionizing the field of healthcare analytics, as they have allowed handling and interpreting extensive amounts of clinical data. Electronic health records, medical imaging systems, laboratory tests, and patient monitoring devices are generating huge datasets in healthcare institutions. These sources of data offer good prospects of coming up with predictive models that can aid the health care practitioners to make sound clinical judgments [18]. General machine learning algorithms are especially helpful when one aims to detect patterns and relationships in complex healthcare data sets that do not necessarily reveal themselves to standard analysis tools. Some machine learning applications to healthcare have been made, such as logistic regression, decision trees, random forests, support vector machines, and deep neural networks. Some of the most common tasks that have been carried out using these algorithms include the detection of diseases, prediction of mortality, prescribing of treatment, the assessment of patient risk and predicting hospital readmission [19]. Clinical outcomes can be predicted by the use of predictive models generated on the basis of patient characteristics, medical history, laboratory results, and interactions with treatments using the techniques. Predictive analytics has found its significance in critical care settings including intensive care units (ICUs) where caregivers identify high-risk patients at the risk of complications or death to intervene in advance. Although machine learning models have promising potential in their application to healthcare data, there are a number of limitations to their application [20]. The fact that many predictive models are not interpretable is one of the primary issues of concern. State of the art machine learning and deep learning algorithms tend to be black-box systems, i.e. give predictions without a clear description of how they came to their conclusions. In the healthcare setting, clinicians need clear and understandable systems to make sure that the recommendations provided by AI are potentially accurate and clinically significant [21]. The other limitation is that most machine learning methods are mainly based on numerical data and can not generate the complex relationship between medical terms (diseases, symptoms, medications, and clinical procedures). With the rise of the data-driven healthcare system, the requirement to develop smart analytical systems integrating predictive and structured knowledge representation is on the rise [22]. By incorporating domain and machine learning models, it would have the potential to increase their interpretability, reliability, and efficacy in aiding clinical decision-making.

B. Medical Knowledge Representation Graphs Knowledge Graphs

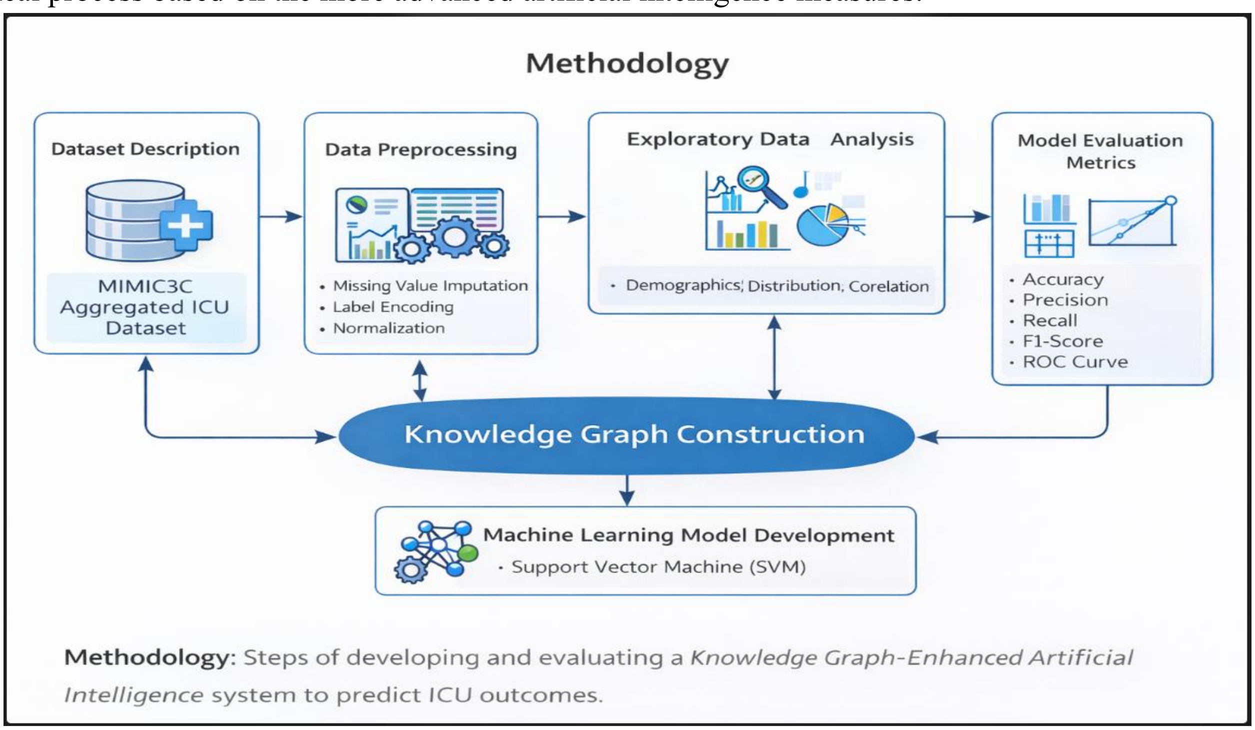
Knowledge graphs have become a promising method of modeling structured knowledge and complicated-relationships in large data sets [23]. Knowledge graphs in the healthcare sector are employed to store medical data in a form of relationship and network of entities. These entities can be patients, disease, symptoms, medication, laboratory tests, or medical procedures with relation between entities indicating the interaction between the entities [24]. The knowledge graphs present a holistic conceptualization of the relationships that are realized within the healthcare systems by organizing medical knowledge in this manner. Knowledge graphs in healthcare allow combining dissimilar data in healthcare, such as clinical records, biomedical databases, research literature, and healthcare guidelines. With such integration, the representation of healthcare information in a unified structure becomes possible, which can be evaluated more efficiently and rationally [25]. Semantic interpretation of medical information using knowledge graphs also ensures contextual connections of clinical entities. As an example, a disease associated with a particular symptom, a drug associated with a particular disease, or a test done to diagnose a disease are some relationships that can be represented in a knowledge graph. The structured relationships enable the computational models to interpret healthcare information more efficiently and produce meaningful information [26]. The other key benefit of knowledge graphs is that they can increase the interpretability of artificial intelligence systems. Knowledge graphs enable AI models to deliver a description of why they are making their predictions and recommendations as they do by explicitly modeling relationships among medical concepts. It is especially useful in healthcare systems where openness and trust are crucial. Knowledge graphs can be used to perform more sophisticated analytic methods like graph-based learning, semantic reasoning, and relationship discovery [27]. This allows healthcare systems to discover latent relationships within medical data and enhance the overall insight of patient conditions and treatment results, knowledge graphs are beginning to be combined with artificial intelligence models to form intelligent healthcare systems with data-driven learning and structured medical knowledge representation.

C. Predictive Healthcare Analytics and Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) are smart information systems that are utilized and help healthcare professionals to make correct and prompt clinical decisions. These systems process patient data and give recommendations, alerts, or predictions that can be used to support diagnosis, treatment planning, and patient management [28]. The main aim of clinical decision support systems is to enhance the quality of healthcare, decrease medical errors, and improve the outcome of patients by considering evidence-based information to clinicians. As more and more healthcare information gets accessible and more and more computational technology progresses, predictive analytics is now a vital aspect of the contemporary clinical decision support systems. Predictive healthcare analytics is an approach that aims at observing what has previously occurred and the current data to determine any pattern that can be used to predict the clinical outcome [29]. Such predictive models can determine the risk of the disease, hospital readmission, see the first signs of complications, and estimate the risk of patient death. Predictive analytics is important in the intensive care unit setting, which necessitates monitoring of patient conditions and facilitation of early medical interventions in a critical care unit setting like the intensive care unit. Predictive models will be able to recognize patients that need urgent care and specific treatment by examining their demographics, medical history, lab findings, and interaction with treatments [30]. Despite the proven benefits of clinical decision support systems, there are a number of challenges that are encountered with the implementation of these systems. Integration of various healthcare data sources is one of the challenges and in most cases, the information includes both structured and unstructured information [31]. The other issue is the predictive models should be understandable and consistent with clinical expertise. Most conventional decision support systems are based on rule-based or statistical models and are not always able to capture the intricacy of patient care processes. Recent studies have been aimed at trying to overcome these limitations by trying to combine both artificial intelligence methods and structured knowledge representation [32]. Knowledge graphs combined with predictive analytics enable clinical decision support systems to combine medical knowledge, contextual relationships, and data-driven insights in the same way. The accuracy, transparency and effectiveness of clinical decision support systems can be enhanced with this integration which will eventually help healthcare professionals to make more informed decisions and provide better care to patients.

III. Methodology

This study will explain the methodological framework to be adopted in developing and testing the proposed Knowledge Graph-Enhanced Artificial Intelligence system to provide intelligent clinical decision support. The methodology entails data selection, preprocessing data, exploratory analysis of data, development of various machine learning models, and performance analysis [33]. The general workflow will examine the data on the interaction with the ICU patients in order to predict the outcomes of the clinical process based on the more advanced artificial intelligence measures.



This workflow depicts the methodological workflow of knowledge graph enhanced AI clinical prediction systems

The methodology diagram provides the systematic flow of work that will be used in this research to create a Knowledge Graph-Enhanced Artificial Intelligence system to assist with intelligent clinical decision-making. It starts with the description of the data, where the primary source of information used in the analysis is the MIMIC3C aggregated ICU dataset which consists of patient demographics and clinical data. The second step is data preprocessing, which consists of missing value replacement, categorical variable label encoding, and data normalization to make the dataset analysis ready [34]. Once preprocessed, the exploratory data analysis (EDA) is done to analyze the demographic distributions, trends, and associations between clinical variables. It is followed by the knowledge graph construction that is included in the framework and represents the relationships between clinical entities, including patients, diagnosis, and treatment. Lastly, the development of machine learning models based on the Support Vector Machine (SVM) algorithm is conducted and the model is tested based on such metrics as accuracy, precision, recall, F1-score, and ROC curve.

A. Dataset Description

The dataset in this study is the MIMIC3c aggregate dataset, which is based on that of MIMIC-III Clinical Database. The data in the dataset consists of anonymous records of ICU patient admission and consolidated data of hospital interactions. Every record is a single hospital admission that consists of demographic data, the characteristics of admission, and the variables of healthcare interaction [35]. The most important attributes in the dataset are age and gender of the patient, admission data of the patient such as the admission type and the place of admission, clinical diagnosis, insurance cover, and marital status. In addition, there are interaction-based features in the dataset, which describe the severity of medical attention given to patients in the hospital. Such features are the mean number of laboratory tests, medications, imaging records, clinical notes, orders, caregivers, and care units that took part in patient treatment [36]. The main aim of working with this dataset is to forecast the outcome of hospital mortality according to the features of patients and the patterns of their interactions with hospitals. The data set is informative on the topic of patient conduct and operational dynamics in the hospital and so it can be used to formulate predictive healthcare analytics models.

B. Data Preprocessing

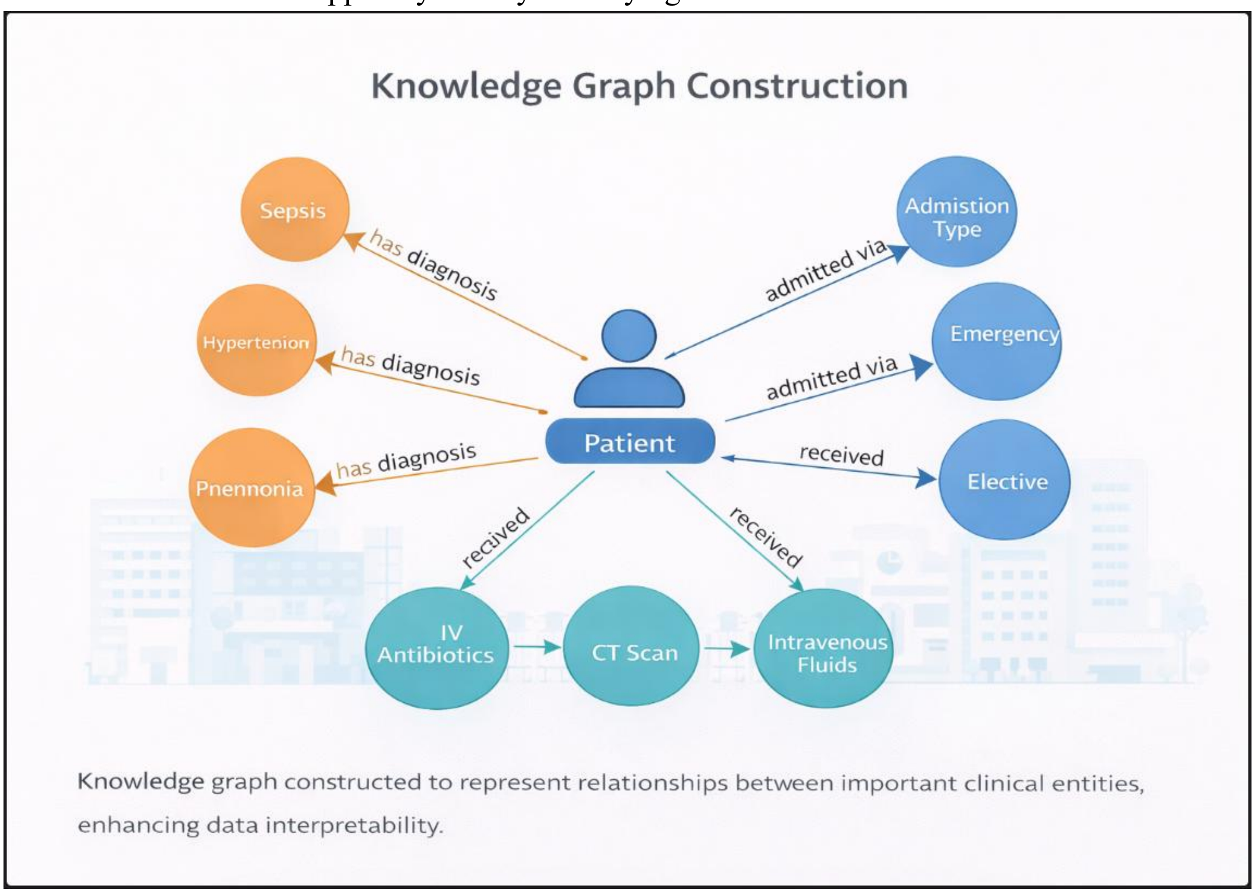
The first thing in machine learning analysis is data preprocessing which prepares the data to be processed. Raw healthcare datasets are usually affected by missing values, categorical variables, and inconsistency which need to be resolved before the development of the models. In this research, a number of preprocessing methods were employed so as to quality control the data and enhance the performance of the models [37]. To begin with, inappropriate methods of data imputation were applied to include missing values in the dataset. Median was used to fill numerical attributes to ensure they are not affected by outliers and categories variables were transformed through encoding [38]. The encoding of labels was done to transform categorical variables (gender, admission type, and admission location) into numerical values that the machine learning algorithms could understand. The dataset was then scaled to prevent the biasing of the learning process by features with varied numeric values. Numerical features were transformed by standardization techniques to a uniform distribution [39]. The data was split into training and testing datasets after preprocessing with a standard split 70/30 ratio of training and testing respectively. This division enabled the model to acquire trends out of the training data and assess predictive performance based on unknown test data.

C. *Exploratory Data Analysis*

To get a feel of the underlying structure and distribution of the dataset, the Exploratory Data Analysis (EDA) was performed. A number of visualizations were created to examine the patient demographics, hospital admission trends, and clinical variables [40]. The age distribution, gender distribution, and the type of admission and length of stay were visualized with the help of histograms and bar charts. EDA was also able to reveal the possible relationship between variables and identify trends that may affect patient outcome [41]. The correlation analysis was conducted to determine the association between various clinical characteristics and identify which factors can play an important role in predictive modeling. These were applied in guiding feature selection and development of models.

D. *Graph Construction of Knowledge*

A graph of knowledge was drawn to show connection among vital clinical objects in the dataset. Knowledge graphs enable the structuring of complex healthcare data as a graph of interconnected nodes and relationships to allow interpreting medical data in a more meaningful way [42]. Patients, diagnoses, the types of admission, and the interactions that occur in healthcare were also considered in this study as the nodes in the graph. Interactions between these entities were established in terms of clinical interactions and hospital records [43]. As an illustration, the patient-has diagnosis, patient-admitted through admission type and patient-received treatment relationships were expressed in the graph format. The given knowledge graph representation will permit applying the structured medical knowledge to the models of machine learning [44]. The knowledge graph facilitates interpretability and smart thinking within the clinical decision support system by identifying correlations between clinical variables.



This diagram depicts a knowledge graph that shows connections among patients and diagnoses, admissions, and treatments

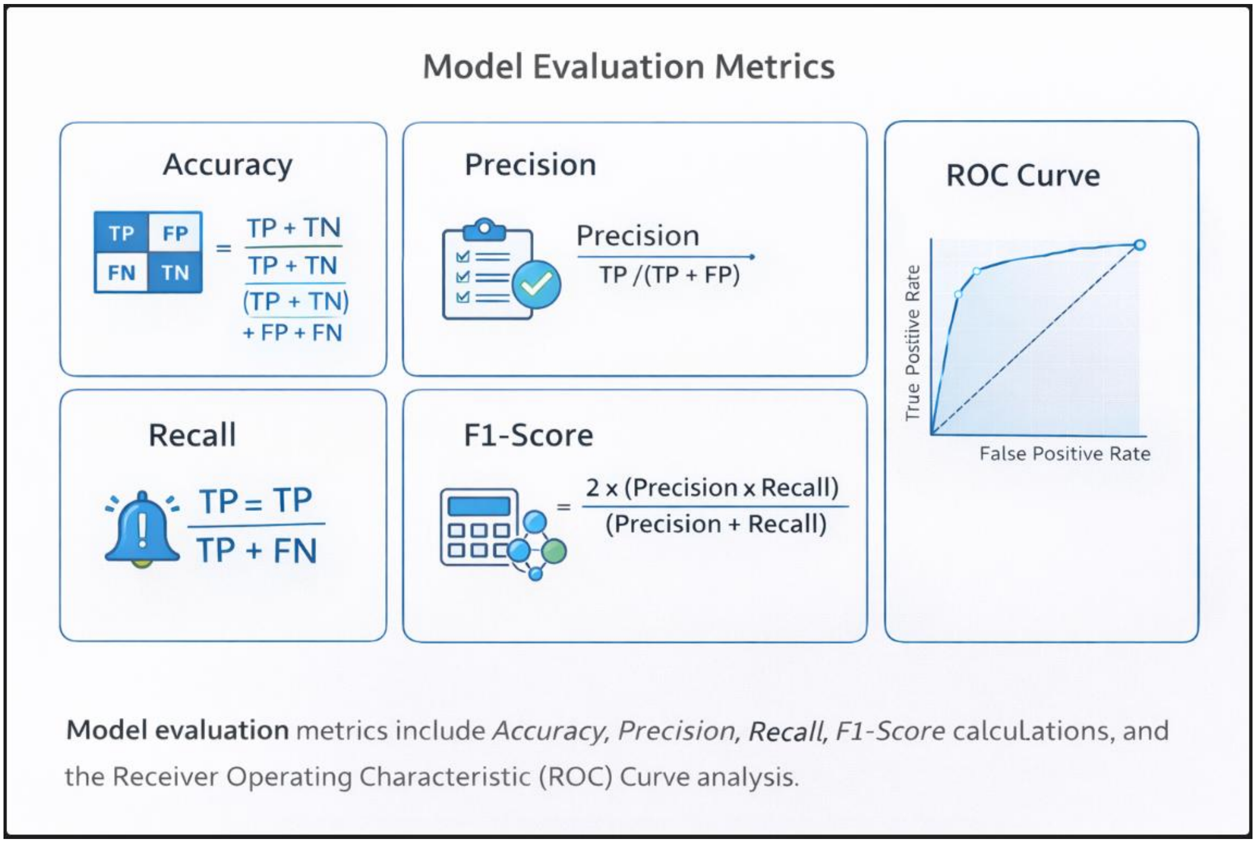
The diagram shows the knowledge graph building mechanism to display the relationship between the significant clinical objects in healthcare information. The patient node is central to the graph and it has various relationships with other clinical entities [43]. The diagnosis nodes on the left side include sepsis, hypertension, and pneumonia, which are linked with the patient by the relationship of his diagnosis. The categories of hospital admission including admission type, emergency and elective are also connected on the right side with the help of the relationship of the type admitted via. The bottom-level entities involving the treatment, i.e., IV antibiotics, CT scan and intravenous fluids are linked by the received relationship creating a formalized depiction of clinical interactions.

E. Development of the machine learning models

A machine learning classification model was created based on the Support Vector Machine (SVM) algorithm to predict patient outcomes. SVM is a supervised learning model that is commonly used to perform different types of classification tasks because it can be utilized to process high-dimensional data and produces strong decision boundaries [44]. SVM model was developed by training the processed data, with the patient features being input variables and mortality outcome being the target variable. In training the model, the two outcome classes are disaggregated by the identification of an optimal hyperplane that increases the margin between the two outcome classes [45]. This method allows the model to categorize new patient records through acquired patterns on the training records. After the model was trained, it was applied to the test dataset in order to produce patient outcome predictions. These predictions were then measured by different performance measures as a measure of the effectiveness of the model.

F. Model Evaluation Metrics

In order to test the performance of the predictive model, a number of conventional classification measures were applied. Such measures are accuracy, precision, recall, F1-score and Receiver Operating Characteristic (ROC) curve. Measure [46] the overall ratio of correct classification of prediction is the accuracy. Precision ascertains the number of the predicted positive cases which are correct and recall the capability of the model to find the actual positive cases. F1-score gives a balanced value that gives both precision and recall. Also, the confusion matrix was constructed to visualize the distribution of the true positives, true negatives, false positives and false negatives [47]. The discriminative ability of the model at varying classification thresholds was tested using the ROC curve. In examining these measures of evaluation, the research measures the level of efficiency of the proposed AI-based prediction framework and how it can be used in clinical decision support framework systems.

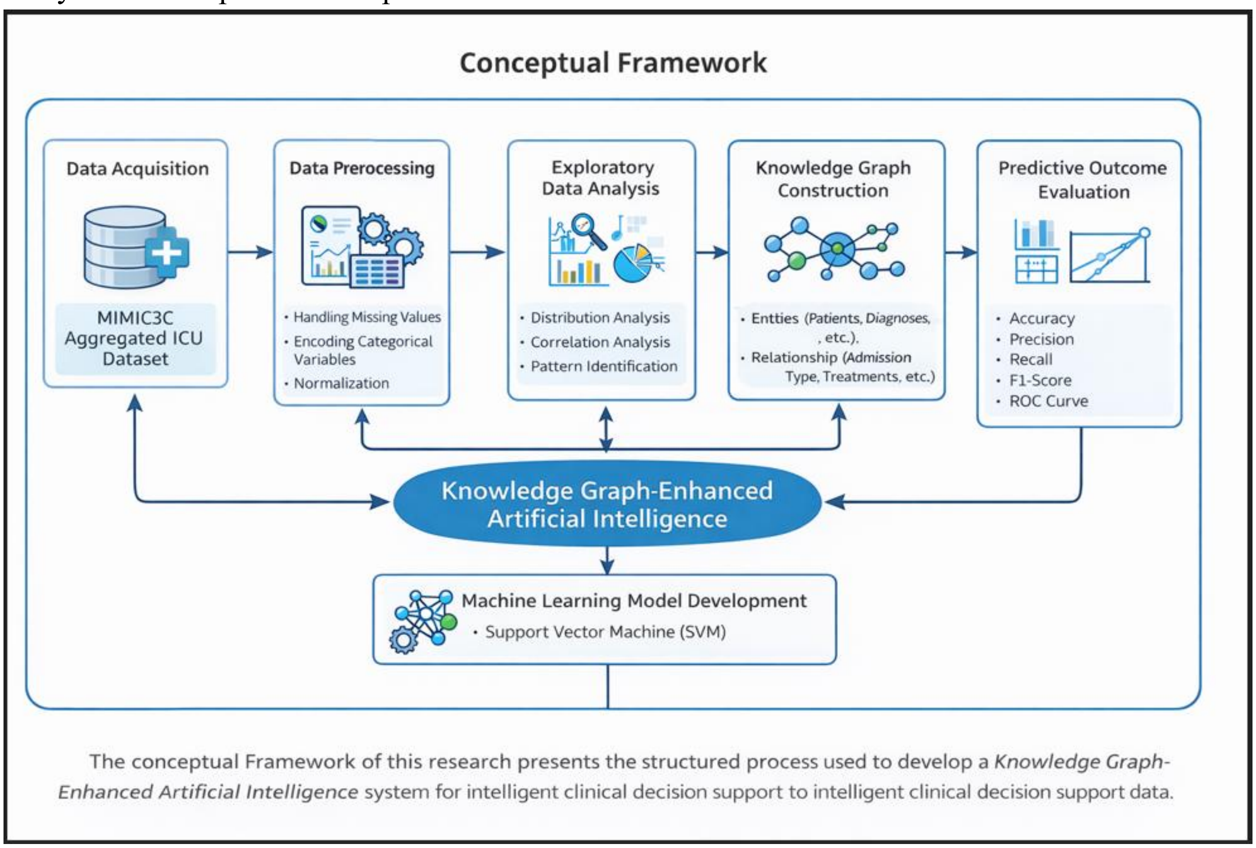


This diagram shows the machine learning model evaluation metrics of clinical prediction performance

The diagram demonstrates the model evaluation metrics that are applied in the measurement of the performance of the machine learning model developed in this study. It demonstrates major classification measures such as accuracy, precision, recall, F1-score, and ROC curve, which are the typical metrics of the predictive models in healthcare analytics. Accuracy is the measure of total correctness of the predictions using true and false values. Precision [48]. This measures the number of correctly predicted positive cases of all the predicted positive cases. Recall is the measure of the model to identify the actual positive cases. The F1-score is a balance between the precision and recall measure of performance. The ROC curve is a visual model used to illustrate the capability of the model in differentiating between positive and negative classes.

IV. Conceptual Framework

The theoretical framework of the current study introduces the stepwise framework that was adopted to build an intelligent clinical decision support Knowledge Graph-Enhanced Artificial Intelligence system. The framework combines healthcare data analytics, knowledge representation, and machine learning tools to analyze the data of ICU patients and identify clinical outcomes. This will start with data collection of the MIMIC3c aggregated dataset, which includes the anonymized records of ICU patient admissions with demographic data and patient admissions, diagnosis data, and hospital interaction data in the form of laboratory test data, medication data, imaging reports, and caregiver activities. Such data elements can give significant information about the health conditions and treatment patterns of the patients in the hospitals [51]. Data preprocessing follows data collection to prepare the dataset to be analyzed through pre-processing of missing values, encoding the categorical variables to numerical format and normalization of the data to have all data with the same data scale [52]. After cleaning and standardizing the dataset, exploratory data analysis (EDA) is performed in order to provide an analysis of the distribution of variables and some trends in patient demographics, types of admission, and the length of hospital visit. The visual methods of analysis that are employed to gain insights into the correlation between clinical variables include histograms, bar charts, and correlation matrices [53]. After the discovery phase, a graph representation of knowledge is created to process the information that characterizes the relationship between important clinical entities, like patients, diagnoses, the type of admission, and treatment interaction. Entities in this type of graph are represented by nodes and the relationship between them illustrated by an edge, which allows a structured representation of medical knowledge and contextual relationships. Once the knowledge representation has been created, a machine learning classifier is constructed with the help of the Support Vector Machine (SVM) algorithm that could be used to predict the patient outcome on the basis of clinical characteristics and interaction patterns [54]. The model is based on the patterns of the past ICU records and categorizes records of patients as either survival or mortality. Conclusively, the predictive model is tested by conventional evaluation measures such as accuracy, precision, recall, F1-score, confusion matrix, and ROC curve, which are used to evaluate the success of the model in predicting patient outcomes [55]. This conceptual framework illustrates that the combination of healthcare data, knowledge graphs, and artificial intelligence methods can help to develop intelligent clinical decision support systems that enhance predictive healthcare analytics and help healthcare professionals to make informed medical decisions.



This diagram represents knowledge graph-enriched clinical decision support workflow

The proposal Knowledge Graph-Enhanced Artificial Intelligence system to provide intelligent clinical decision support has a conceptual framework diagram as depicted in the figure below: It starts with the data acquisition where the MIMIC3C aggregated ICU data is used, and it includes the patient demographic and clinical data. The data are then processed by data preprocessing which involves dealing with missing values, encoding categorical variables as well as normalization [55]. Exploratory data analysis follows after preprocessing in order to know the patterns and relationships in the dataset. The second phase is constructions of knowledge graphs through which clinical entities and relationships are organized to model medical knowledge. The development of machine learning models based on the Support Vector Machine (SVM) algorithm uses this information [56]. Lastly, the model performance is measured based on accuracy, precision, recall, F1-score and ROC curve.

V. Dataset

A. Screenshot of Dataset

hadm_id	gender	age	LOSdays	admit_type	admit_location	AdmitDiagnosis	insurance	religion	marital_status	ethnicity	NumCallouts
100001	F	35	6.17	EMERGENCY	CLINIC REFERRAL/P	DIABETIC KETOACID	Private	PROTESTANT Q	DIVORCED	WHITE	0.16
100003	M	59	4.04	EMERGENCY	EMERGENCY ROOM	UPPER GI BLEED	Private	NOT SPECIFIED	SINGLE	WHITE	0.25
100006	F	48	12.04	EMERGENCY	EMERGENCY ROOM	COPD FLARE	Private	NOT SPECIFIED	SINGLE	BLACK/AF	0
100007	F	73	7.29	EMERGENCY	EMERGENCY ROOM	BOWEL OBSTRUCTI	Private	JEWISH	MARRIED	WHITE	0.41
100009	M	60	4.88	EMERGENCY	TRANSFER FROM H	CORONARY ARTERY	Private	CATHOLIC	MARRIED	WHITE	0
100010	F	54	4.38	ELECTIVE	PHYS REFERRAL/NO	RENAL MASS LEFT/S	Private	EPISCOPALIAN	MARRIED	WHITE	0.23
100011	M	21	14.38	EMERGENCY	CLINIC REFERRAL/P	MOTOR VEHICLE AC	Medicaid	NOT SPECIFIED	SINGLE	HISPANIC	0.07
100012	M	67	10.08	EMERGENCY	TRANSFER FROM H	CORONARY ARTERY	Medicare	CATHOLIC	MARRIED	WHITE	0.1
100014	F	49	0.63	ELECTIVE	PHYS REFERRAL/NO	RIGHT SHOULDER AI	Medicaid	CATHOLIC	SINGLE	WHITE	0
100016	M	55	6.17	EMERGENCY	CLINIC REFERRAL/P	PNEUMONIA	Medicare	PROTESTANT Q	SINGLE	WHITE	0
100017	M	27	0.67	URGENT	TRANSFER FROM H	OVERDOSE	Medicaid	CATHOLIC	SINGLE	UNKNOW	0
100018	M	55	8.25	ELECTIVE	PHYS REFERRAL/NO	HERNIATED DISC/SI	Private	PROTESTANT Q	MARRIED	WHITE	0.12
100019	M	27	3.17	ELECTIVE	PHYS REFERRAL/NO	AORTIC VALVE DISE	Private	OTHER	MARRIED	WHITE	0
100020	M	58	10.58	EMERGENCY	EMERGENCY ROOM	HYPONATREMIA	Private	CATHOLIC	MARRIED	WHITE	0.09
100021	M	54	60	EMERGENCY	EMERGENCY ROOM	BILATERAL ANKLE F	Medicaid	UNOBTAINABLE	MARRIED	HISPANIC	0.03
100023	M	0	2.33	NEWBORN	PHYS REFERRAL/NO	NEWBORN	Private	CHRISTIAN SCIE	NA	WHITE	0
100024	M	71	6.33	ELECTIVE	PHYS REFERRAL/NO	CORONARY ARTERY	Medicare	NOT SPECIFIED	MARRIED	UNKNOW	0.16
100025	M	0	2.58	NEWBORN	PHYS REFERRAL/NO	NEWBORN	Private	JEWISH	NA	WHITE	0
100028	F	72	6.88	EMERGENCY	CLINIC REFERRAL/P	CHOLANGITIS	Medicare	CATHOLIC	SINGLE	WHITE	0.15
100029	F	0	15	NEWBORN	CLINIC REFERRAL/P	NEWBORN	Private	NOT SPECIFIED	NA	WHITE	0
100030	M	33	15.88	EMERGENCY	EMERGENCY ROOM	PNEUMONIA	Private	PROTESTANT Q	MARRIED	HISPANIC	0
100031	F	81	13.17	ELECTIVE	PHYS REFERRAL/NO	AORTIC ASCENTING	Medicare	CATHOLIC	MARRIED	WHITE	0
100033	M	22	1.46	EMERGENCY	EMERGENCY ROOM	MEDIASTINAL AIR	Private	CATHOLIC	SINGLE	WHITE	0.68
100034	M	68	3.75	ELECTIVE	PHYS REFERRAL/NO	CORONARY ARTERY	Medicare	NOT SPECIFIED	MARRIED	WHITE	0.27
100035	M	36	25.29	EMERGENCY	CLINIC REFERRAL/P	POST ARREST	Medicaid	NOT SPECIFIED	SINGLE	HISPANIC	0.04
100036	F	82	10.04	EMERGENCY	TRANSFER FROM H	CHF	Medicare	CATHOLIC	SINGLE	WHITE	0.1
100037	M	58	46.71	EMERGENCY	EMERGENCY ROOM	WEAKNESS	Private	PROTESTANT Q	MARRIED	WHITE	0.04
100038	F	57	1.83	EMERGENCY	EMERGENCY ROOM	CHEST PAIN	Medicaid	CATHOLIC	SINGLE	HISPANIC	0.55
100039	F	38	28.58	EMERGENCY	CLINIC REFERRAL/P	ABDOMINAL PAIN	Governmer	CATHOLIC	SINGLE	BLACK/AF	0.03
100040	M	30	2.88	EMERGENCY	CLINIC REFERRAL/P	BLUNT TRAUMA	Private	NOT SPECIFIED	MARRIED	BLACK/AF	0.35
100041	M	64	4.25	ELECTIVE	PHYS REFERRAL/NO	CORONARY ARTERY	Private	UNOBTAINABLE	MARRIED	WHITE	0
100044	M	0	32.79	NEWBORN	PHYS REFERRAL/NO	NEWBORN	Governmer	NOT SPECIFIED	NA	WHITE	0
100045	F	69	10	EMERGENCY	EMERGENCY ROOM	CHANGE IN MENTAL	Medicare	CATHOLIC	WIDOWED	WHITE	0.2
100046	F	66	5.67	EMERGENCY	EMERGENCY ROOM	ALCOHOL WITHDRA	Private	CATHOLIC	WIDOWED	WHITE	0
100047	M	56	6.71	EMERGENCY	EMERGENCY ROOM	HYPOTHERMIA;SUB	Medicaid	CATHOLIC	WIDOWED	WHITE	0.15
100050	M	69	6	ELECTIVE	PHYS REFERRAL/NO	CORONARY ARTERY	Medicare	CATHOLIC	MARRIED	WHITE	0.17

hadm_id	NumDiagnosis	NumProcs	AdmitProcedure	NumCPTevents	NumInput	NumLabs	NumMicroLabs	NumNotes	NumOutput	NumRx	NumProcEvents	NumTransfers	NumChartEvents	ExpiredHospital	TotalNumInteract	LOSgroupNum
100001	2.59	0	na	1.3	25.12	43.44	0.65	0.05	5.19	14.91	1.13	0.65	398.7	0	493.89	2
100003	2.23	0.99	Endosc co	1.98	13.61	55.94	1.24	1.59	5.45	7.18	0.99	1.24	373.02	0	465.71	2
100006	0.75	0.17	Non-invas	0.83	11.46	33.39	0.33	0.15	4.15	6.23	0	0.33	286.21	0	344	4
100007	0.69	0.27	Part sm bo	0.69	20.3	32.24	0.69	0.17	9.05	11.52	0	0.96	526.06	0	603.05	2
100009	3.69	0.82	Aortocor b	2.25	20.49	50.61	0.61	0.34	16.19	25	2.87	2.05	554.92	0	679.84	2
100010	1.14	0.68	Nephrour	1.83	6.62	30.59	0	0.11	7.99	9.13	1.14	0.91	448.63	0	509	2
100011	0.97	1.04	Debrid op	3.13	62.38	43.46	1.88	0.21	18.01	9.94	4.1	0.21	1337.1	0	1482.53	4
100012	1.09	0.4	1 int mam	1.09	19.54	38.49	0.3	0.15	15.48	14.48	2.28	0.6	524.11	0	618.11	3
100014	12.7	4.76	Rep recur	3.17	0	0	0	0	0	0	0	4.76	0	0	25.39	1
100016	1.78	0.81	Temporar	2.43	25.93	34.36	0.81	0.21	16.53	10.05	1.13	0.49	1221.4	0	1315.92	2
100017	11.94	2.99	Non-invas	0	19.4	74.63	0	15.6	7.46	0	0	2.99	647.76	0	782.77	1
100018	3.52	0.85	Oth cerv f	2.3	37.33	53.7	0.36	0.85	9.82	11.52	2.06	0.48	728.85	0	851.76	3
100019	1.26	0.95	Opn/oth r	0	0	0	0	0.2	0	0	0	1.26	0	0	3.67	1
100020	1.7	0	na	1.7	1.42	32.23	0.66	0.37	1.8	5.2	0.19	0.47	87.33	0	133.16	3
100021	0.48	0.13	Appl ext f	1.22	2.38	23.2	0.78	0.02	0.7	5.12	0	0.12	82.22	0	116.4	4
100023	2.15	0.86	Circumcisi	0	0	11.16	0.43	0.37	0	0	0	1.72	33.91	0	50.6	1
100024	1.74	0.47	1 int mam	1.26	15.17	36.02	0.32	0.18	5.85	16.9	2.21	0.63	214.06	0	294.97	2
100025	3.1	2.33	Insert end	0	14.73	0	0	1.5	0	0	0	1.94	323.26	0	346.86	1
100028	1.31	0.73	Laparosco	1.45	8.28	34.45	1.02	0.23	5.81	11.34	1.45	0.58	252.03	0	318.83	2
100029	0.27	0.07	Entral infu	0	11.73	2.13	0.07	0.3	0.13	0.33	0	0.27	445.27	0	460.57	4
100030	0.38	0.06	Closed br	0.82	10.77	35.71	0.88	0.09	0.57	0	0	0.25	111.15	0	160.68	4
100031	0.68	0.46	Opn aorti	0.3	72.44	43.43	0.15	0.13	11.54	7.67	0	0.61	612.76	0	750.17	4
100033	1.37	0.68	Other bro	0.68	56.85	59.59	2.74	3.75	10.27	27.4	0	2.05	837.67	0	1003.73	1
100034	2.13	0.8	1 int mam	1.33	35.2	53.6	0.53	0.78	14.93	20.8	4.27	1.33	563.47	0	699.44	1
100035	1.03	0.16	Bronch/lu	1.66	33.65	38.91	0.71	0.04	9.77	6.01	1.3	0.2	574.89	0	668.37	4
100036	1.69	0.3	Opn/oth r	0.1	30.08	43.53	0.2	0.21	8.76	8.07	0	0.5	476.89	0	570.43	3
100037	0.45	0.28	Interrupti	1.71	2.4	62.11	1.01	0.07	0.75	4.88	0.49	0.13	95.14	0	169.46	4
100038	5.46	0.55	Venous ca	0.55	18.58	67.21	1.09	2.98	6.01	12.02	0	2.19	372.13	0	489.32	1
100039	0.66	0.17	Percu abd	1.61	8.01	41.11	0.31	0.03	4.72	4.02	0.31	0.17	184.36	0	245.51	4
100040	0.69	0	na	2.08	15.97	36.11	0.35	1.2	9.72	16.32	2.78	1.39	471.88	0	558.84	1
100041	1.88	0.71	Aortocor b	0	34.35	40.47	0	0.5	11.53	0	0	1.18	248.47	0	339.09	2
100044	0.3	0.21	Insert end	0	26.29	3.54	0.06	0.17	1.1	1.07	0	0.18	499.45	0	532.37	4
100045	1.2	0.9	Hemodial	2.3	25.6	63.4	4.6	0.4	5.8	8.4	0	0.3	814.3	0	927.4	3
100046	1.41	0.18	Egd with c	1.06	32.28	56.26	0	0.31	5.64	8.99	0	0.71	206.7	0	313.54	2
100047	2.53	0.6	Cont inv n	1.19	14.31	0	0.3	0	5.81	17.44	2.09	0.45	327.27	0	372.14	2
100050	1.67	0.67	Opn/oth r	0.17	34.5	43.33	3.67	0.58	6.83	16.33	0	1	356.17	0	465.09	2

mimic3c

(Source Link: https://www.kaggle.com/datasets/drscarlat/mimic3c)

B. Dataset Overview

The dataset in this study is the MIMIC3C aggregated dataset that is based on the famous MIMIC-III (Multiparameter Intelligent Monitoring in Intensive Care) patient clinical database. The data is anonymized patient history records sampled in intensive care unit (ICU) admissions and is useful in our study of clinical trends and predictive healthcare development. The dataset is structured in aggregated format in which one record stand denotes one hospital admission and consists of multiple demographic, administrative and clinical interaction characteristics pertaining to patient care. The main goal of applying this set of data to the study is to examine the characteristics of ICU patients and create a model of artificial intelligence to assist in the process of making smart clinical decisions [57]. The demographic characteristics in the dataset, including the patient age, gender, marital status, religion, and their insurance details give an insight on the population characteristics of the ICU patients. Along with the demographic data, the data includes the hospital admission data such as admission type, administration site, and admission diagnosis, which would be used to explain the situations that led to the patient being admitted to the hospital. The length of stay (LOSdays) is one of the important aspects that were included in the dataset, and it is the number of days a patient stayed in the hospital and served as an indicator of the complexity of the medical situation a patient had and the volume of healthcare facilities needed when treating the patient [58]. There is also the data of the aggregated interaction between patients and healthcare providers upon the hospital stay. These metrics of interaction are the number of laboratory tests conducted per day, microbiology tests, intravenous medications, non- intravenous medications, imaging reports, clinical notes, medical orders, the caregivers, and care units visited [59]. Such features are the severity of clinical measures of interventions and healthcare processes connected with every patient admission. Patterns with regards to patient conditions, complexity of treatment, and dynamics of workflow in the hospital can be identified with such interaction data. The dataset also has a hospital mortality label which represents whether the patient survived or died in the process of hospitalization which is the target variable of the classification problem of the study [60]. Taking into consideration the fact that the dataset is identified and aggregated, it does not violate the privacy of patients and still is rather informative when it comes to healthcare analytics. The data is suitable to be used in machine learning projects, such as mortality prediction or clinical decision support because its various clinical and administrative variables provide a comprehensive description of the interactions with patients at the ICU and hospital admissions properties.

VI. Results

The findings of this research prove the efficiency of the suggested artificial intelligence platform to process the ICU patient data and forecast the clinical outcomes [1]. Exploratory data analysis presented valuable information about patient demographics, hospital admission, and visitation patterns as well as length of stay distributions in the data. Various performance measures such as accuracy, precision, recall and F1-score were used to test the predictive model. There was a high level of accuracy and precision in the model, which implies that it is able to classify most patient outcomes correctly [2]. The existence of the ROC curve also indicated the good discriminative power of the model in differentiating the cases of survival and mortality. The correlation analysis was used to determine the relationship between clinical features, which is useful in selecting features [3]. The findings show that the suggested strategy can facilitate intelligent clinical decision-making and enhance predictive healthcare analytics.

A. Distribution of ICU Patients by Age

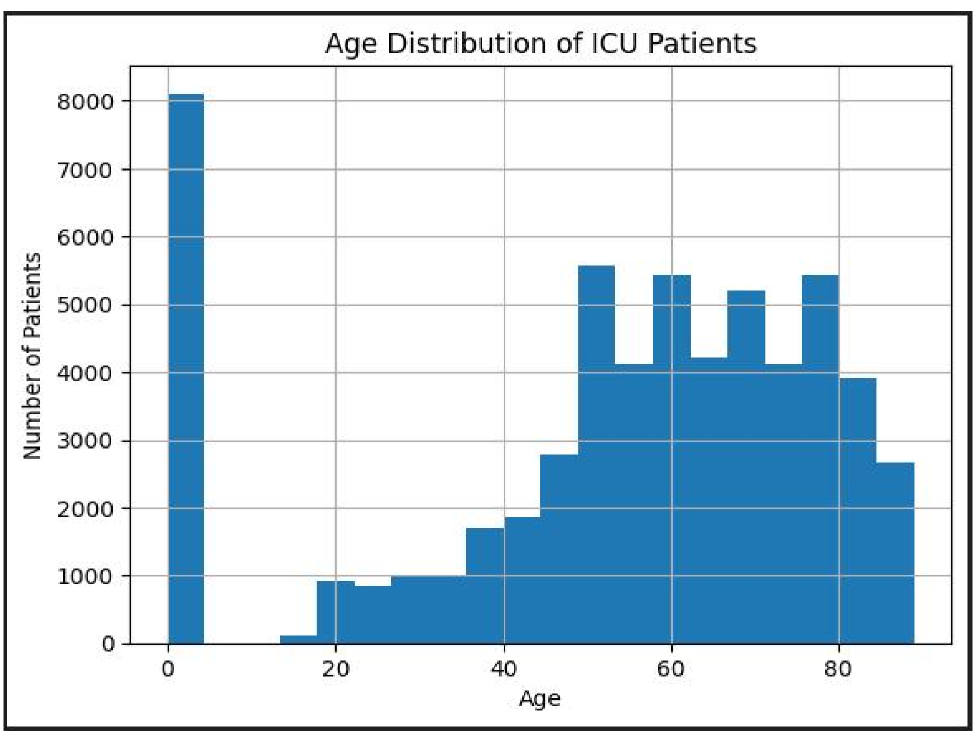


Figure 1: This image illustrates Age distribution of ICU patients with more admissions of middle-aged and older people

Figure 1 shows the distribution of the age of patients in the ICU dataset, which shows the frequency of the admissions by the age groups. Histogram indicates that the ICU admission is distributed over a large age group: newborn patients are included through to the old age group. The distribution however shows that a significant percentage of the patients that are admitted to the ICU are middle-aged and elderly, especially between the age of about 45-80 years. The trend implies that older people are more likely to need intensive medical treatment as they have more chronic diseases, their physiological functions deteriorate more, and they are prone to serious medical conditions, which are more severe [4]. Another spike is observed in the histogram at age zero, which represents the newborn admissions, indicating that there are neonatal cases represented in the dataset. However, there are neonatal admissions but the rate of the neonatal admissions is significantly lower than the rate of adult ICU admissions. One more valuable point made by the figure is that the count of the ICU admissions slowly rises with the younger ages of adults and peaks at the late middle-age and the elderly age groups and is somewhat lower in the oldest age groups [5]. The trend brings out the increased burden of healthcare with aging populations as the aged are more susceptible to complications that need extreme monitoring and care. The distribution also offers practical information on predictive healthcare analytics especially in mortality prediction models where age is frequently a contributing factor to patient outcomes [6]. Age structure of patients in ICU assists researchers and health care experts to detect the demographic trends and come up with more precise foreseeable models in clinical decision making [7]. Demographic data, including age, can be combined with other clinical characteristics in the framework of knowledge graph-based artificial intelligence systems to enhance the predictive healthcare model performance and interpretability.

B. ICU Gender Distribution Analysis of ICU Patients

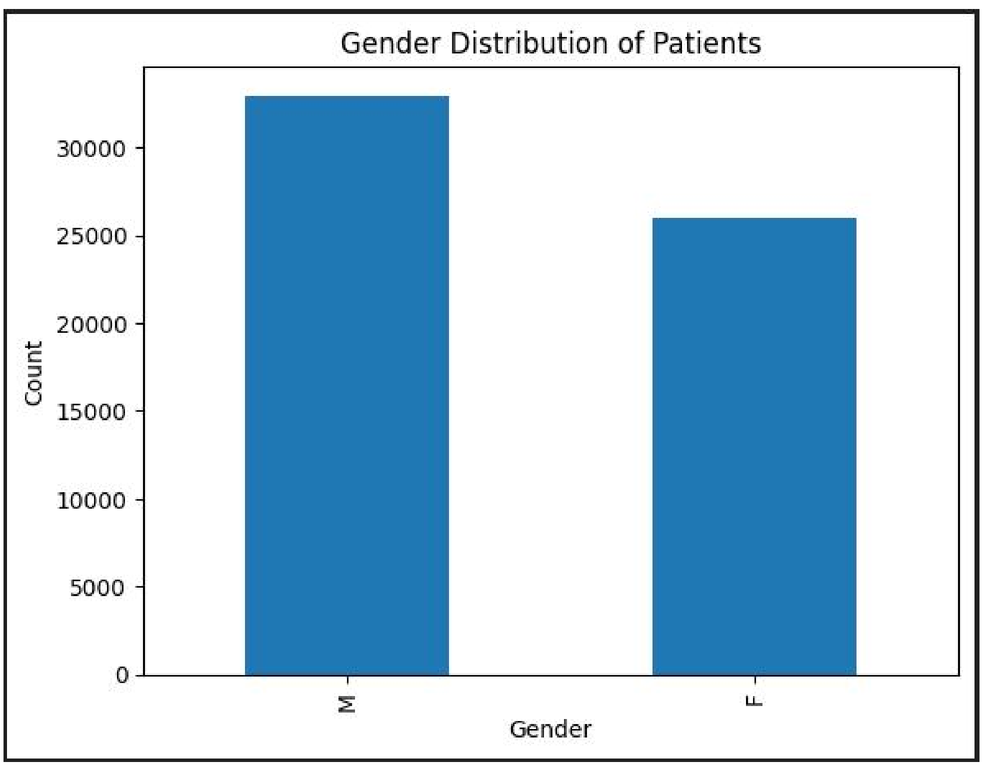


Figure 2: This image depicts the Gender distribution of ICU patients with slightly more admissions of the male patients

Figure 2 shows the gender distribution of patients that were included in the dataset of ICU. The bar chart will be used to compare the admission of men and women into the intensive care unit, which will give some insights into the demographics of the dataset. Based on the visualization, one can see that the number of male patients occupying the ICU bed is a bit higher than that of female patients [8]. The dataset presents a representation that approximates to thirty-three thousand male patients and about twenty six thousand female patients, which means that male patients are the majority in this dataset in the ICU. Such a distinction implies that male patients might be at a greater risk of having to receive an intensive medical treatment based on multiple health-related and physiological causes. A number of clinical studies have shown that men are known to be at risk of some cardiovascular, respiratory and lifestyle related diseases which can be the cause of high ICU admission [9]. Conversely, the patients who are female representatives are also underrepresented in the dataset, but their total percentage is relatively less. This sex ratio gives valuable demographic data that can be used to aid further research in predictive healthcare models [10]. The study of gender trends in ICU admissions may be used to enhance the quality of artificial intelligence models that are applied to predict mortality and assess clinical risks. Gender may be a valuable demographic characteristic in machine learning algorithms since there can be biological variations and health behaviors between men and women that can affect disease progression and reaction to the treatment [11]. Gender information may be linked with other clinical entities, including diagnoses, treatments, and outcomes when incorporated into a knowledge graph-enhanced artificial intelligence platform to get deeper insights into patient characteristics. The analysis of gender distribution is an important step on the way to building the reliable predictive models of intelligent clinical decision support systems.

C. Analysis of Distribution of Hospital Admission Types

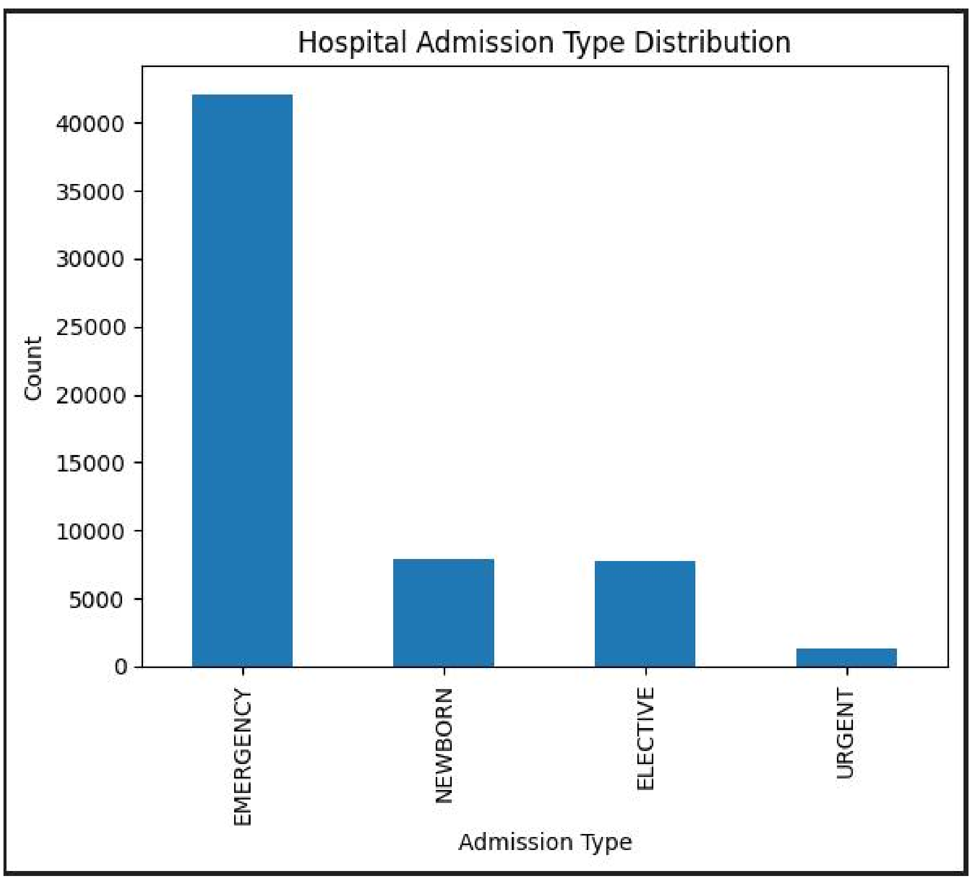


Figure 3: This image illustrates to the Distribution of ICU admissions the prevalence of the emergency cases in this category, compared to other admission types

The distribution of the types of hospital admission in patients of the ICU dataset are shown in figure 3. The bar chart will classify the admissions by the four major categories: Emergency, Newborn, Elective, and Urgent, and the frequency of each will be presented. Based on the visualization, it can be seen that the entry of emergency admissions is by far the highest percentage of the ICU entries. The emergency admissions are much more than the other categories, meaning that the majority of the patients are hospitalized at the ICU because of sudden or urgent medical conditions that need immediate care [12]. The given tendency underlines the character of intensive care units that mostly work with patients with the emergencies of the most serious health problems - cardiac events, respiratory failures, traumas, or acute infections., elective admissions contribute to fewer cases of the ICU. Usually, elective admissions are to be undertaken when the patients are already planning to undergo medical or surgical procedures that involve postoperative care of the ICU. The newborn admissions are also a noticeable number in the dataset which are neonatal cases that need special care, which is in most cases, as a result of complications during birth or being born prematurely. In the meantime, urgent admissions seem to be the least common group in the data. Urgent cases are usually those that involve medical care that is urgent but the conditions of the patients are not as life threatening as an emergency case [13]. The high proportion of emergency admissions indicates that ICU resources become mostly associated with the management of acute and unforeseen medical incidents. The issue of admission type distribution is significant to healthcare analytics as it allows gaining insights into the workflow patterns and patient care needs in hospitals. In predictive healthcare models, approach to admission may be a very important factor that affects patient outcomes, such as the risk of hospital mortality [14]. Adding the information about the type of admission to knowledge graph-based models of the artificial intelligence can enhance the capacity of the clinical decision support system to interpret the severity of illnesses and deliver more successful healthcare planning and interventions approaches.

D. Length of Stay Distribution Analysis

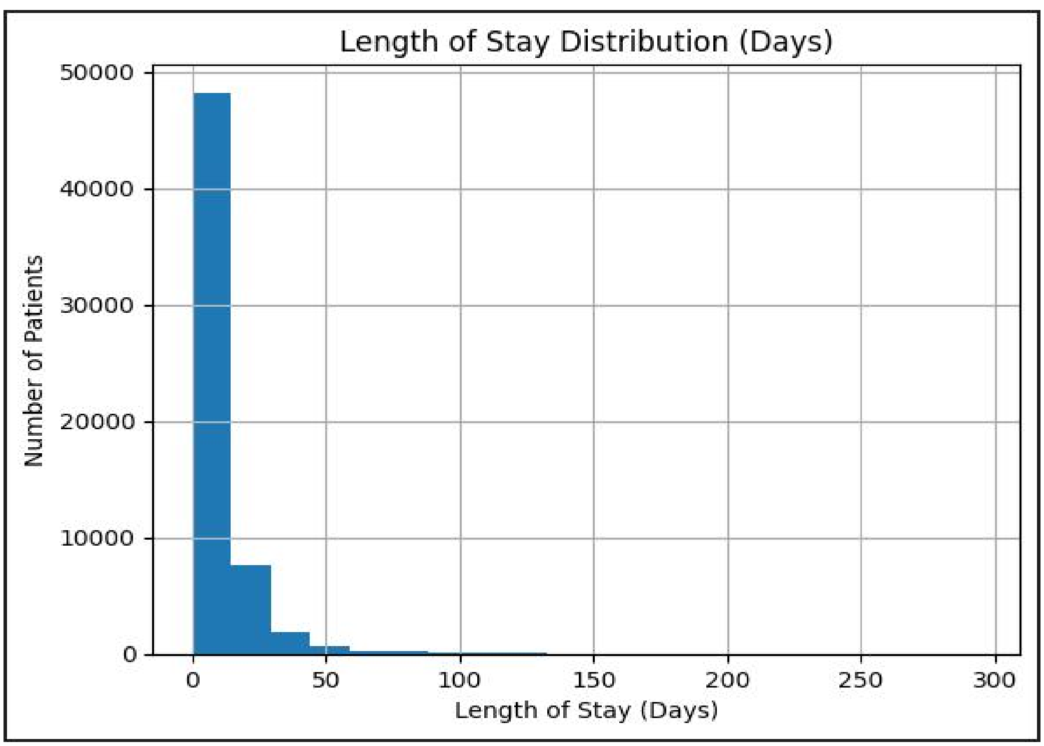


Figure 4: This image represents the Distribution of hospital length of stay with most of the patients having less ICU stay

Figure 4 represents the length of stay (LOS) of the patients in the hospital expressed in days. The histogram provides the distribution of the ICU patients with respect to their days of stay in the hospital. Based on the visualization, it is evident that most patients stay relatively short and there is a huge concentration of cases during the initial few days of admission. The general patients seem to spend below about 20 days in the hospital implying that a good number of ICU admissions are short-term intensive care or treatment followed by discharge or admission to other hospital units [15]. The histogram is extremely skewed to the right, that is, the majority of the patients will have shorter hospital stays but few patients will have longer hospital stays. These more extended stays (lasting more than several weeks or even months in some instances) are normally indicative of patients of extreme medical complexities, chronic conditions, or complicated rehabilitation procedures taking up extended intensive care and treatment [16]. The reduction in the cases with the length of stay underscores the infrequency of extremely long hospitalizations that happen in ICUs. Knowing the length of stay at the hospital is significant to healthcare analytics as it gives an insight into patient recovery patterns, the use of resources in the hospital and the efficiency of the healthcare services [17]. Length of stay may also be an useful predictive characteristic in predictive healthcare models, because a longer hospital stay is sometimes linked to greater severity of disease or complication or mortality risk. LOS may be connected with other clinical variables, like admission type, diagnosis, and treatment interventions in the framework of knowledge graph-based artificial intelligence models to facilitate a more profound analysis of patient outcomes [18]. As such, hospital stay time analysis would aid in better comprehension of patient care dynamics as well as allow the creation of more reliable clinical decision support systems.

E. Analysis of Receiver Operating Characteristic (ROC) Curve of SVM Model

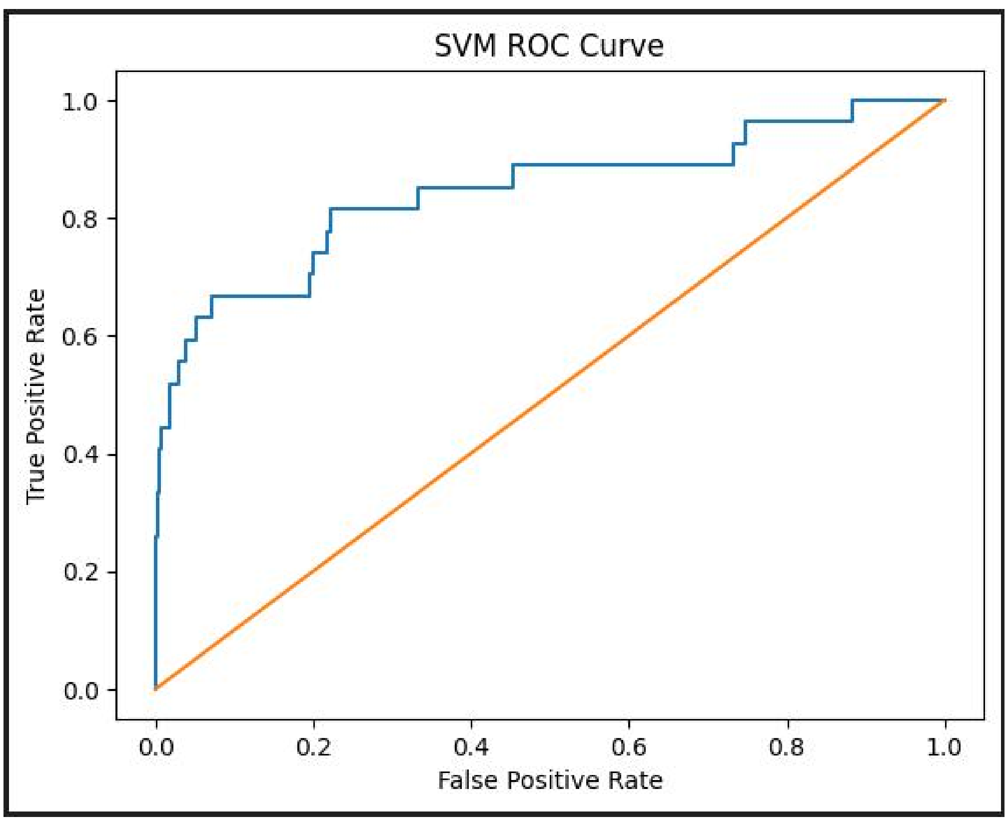


Figure 5: This image illustrate that the SVM model works with ICU mortality risk prediction

The figure 5 shows the Receiver Operating Characteristic (ROC) curve obtained on the Support Vector Machine (SVM) model that was used to predict mortality in the ICU dataset. ROC curve is one of the evaluation tools that have been extensively used in determining the effectiveness of classification models, especially in healthcare predictive analytics. It plots the True Positive Rate (TPR) or sensitivity versus the False Positive rate (FPR) at varying levels of classification threshold. The line in the figure is at the diagonal and it indicates the performance of a random classifier, one where one simply makes predictions by chance. Contrarily, the blue curve indicating the SVM model is far away on top of the diagonal line, which implies that the model is far much better compared to the random guessing. The positive slope of the ROC line proves that the model is capable of a good distinction between positive and negative classes which in this instance are patients with a high and low risk outcome. The closer the curve is to the top-left corner of the graph, the more sensitive it is, and the lower the false positive rates, which are the positive qualities of predictive models in the clinical setting. This action shows that a high percentage of positive results can be accurately classified by the SVM model and few error instances are noted [19]. The curve shape of the ROC indicates that the available clinical features in the dataset can be well discriminated by the classifier to predict the patient outcomes. This predictive accuracy is necessary in healthcare decision support systems to help clinicians with risky patients detect them and achieve timely medical care. The ROC analysis thus proves that the SVM-based predictive model exhibits effective classification and is possible to assist with intelligent clinical decision-making once implemented with knowledge graph-enhanced artificial intelligence models.

F. Metrics Analysis Model Evaluation

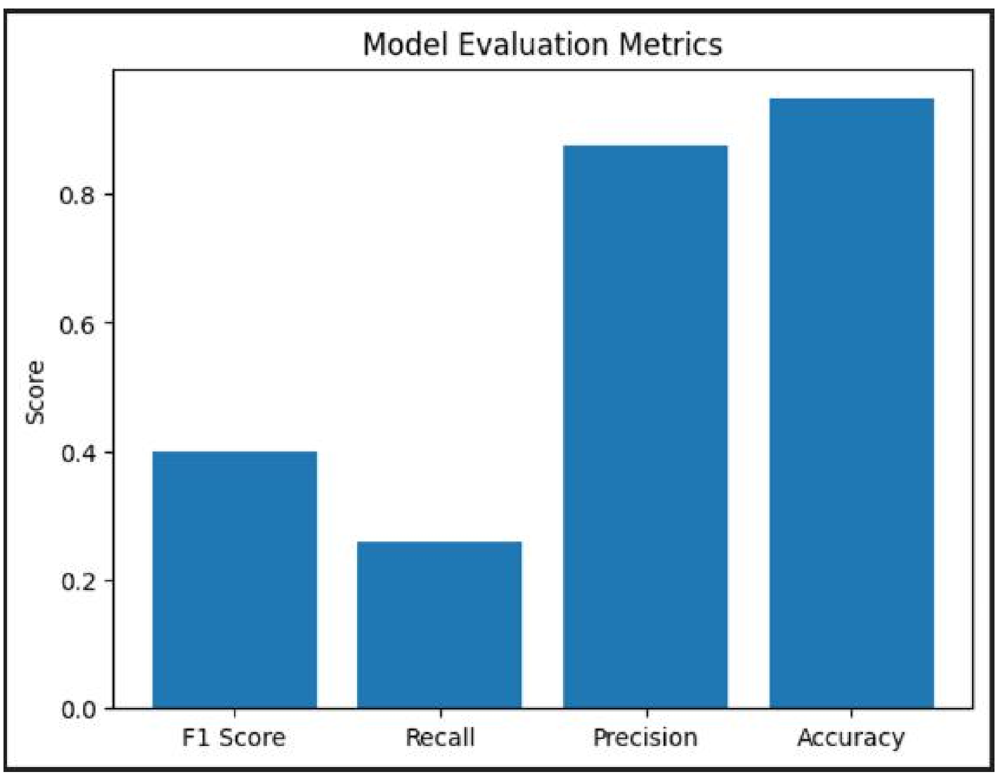


Figure 6: This image demonstrates accuracy, precision, recall, and F1-score of predictive model performance

The results of the evaluation of the predictive model with many standard performance measures, such as F1-score, recall, precision, and accuracy, are shown in Figure 6. These measures are typically applied to determine the efficiency of machine learning models, especially in healthcare prediction tasks in which the classification performance should be evaluated carefully. As presented by the bar chart, the model has recorded the best result in accuracy by recording around 0.93 which implies that most of the predictions produced by the model were accurate. High accuracy implies that the predictive system is capable of making good distinctions between various outcome classes in the sample. Precision also portrays a strong value of about 0.88 and this value shows that the model contains a high fraction of correctly predicted positive cases among all predicted positive cases. This becomes especially significant when used in clinical prediction settings where high accuracy decreases the chances of false alarm and unwarranted medical treatment. F1-score with a compromise between precision and recall is revealed to be approximately 0.40. This value demonstrates a harmonic relation between the correctly identified positive cases and sensitivity of the model to detect the positive cases. At the same time, the recall value is rather low, about 0.26, which means that this model can actually identify only a part of the positive cases. Reduction in recall might indicate that the model is missing some of the true positive cases [20]. This measure is vital in healthcare applications since such patients might miss high-risk individuals and this may lead to impact on patient outcomes. In general, the figure shows that the predictive model works well in the accuracy and precision but still needs some further optimization in order to achieve better recall and balance between the evaluation metrics [21]. These findings shed some significant light on the strong and weak sides of the existing model and reveal the possibilities of future optimization of predictive performance of knowledge graph-enhanced clinical decision support systems.

G. Comparison of Model Evaluation Metrics

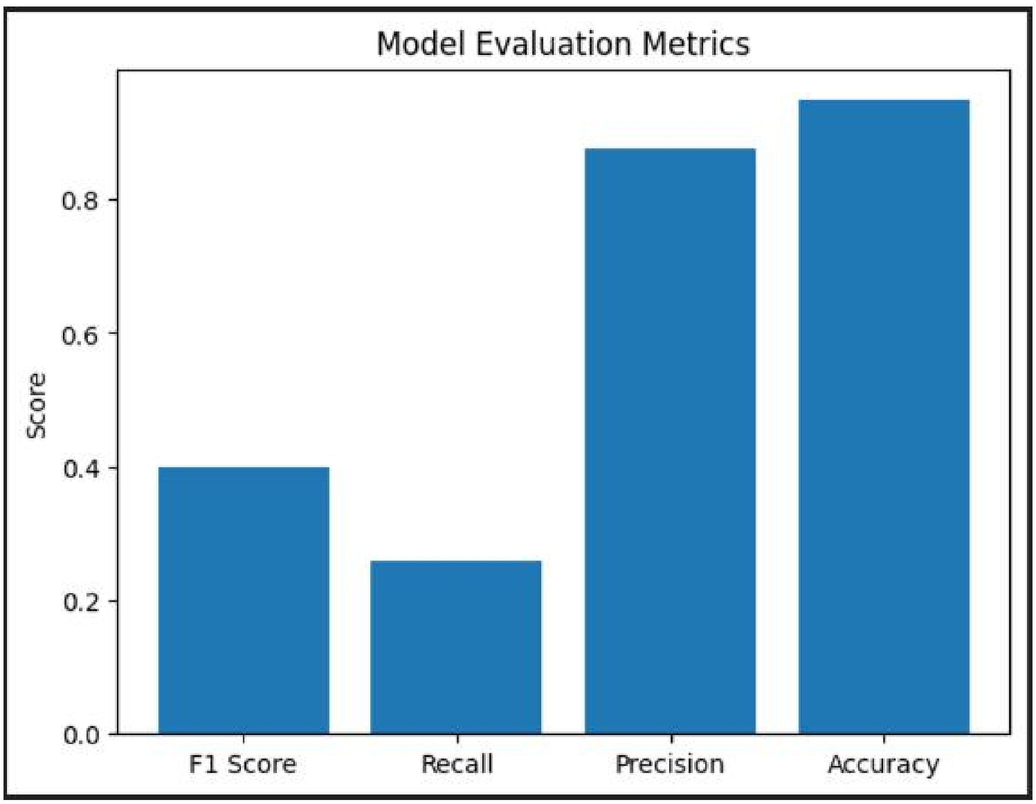
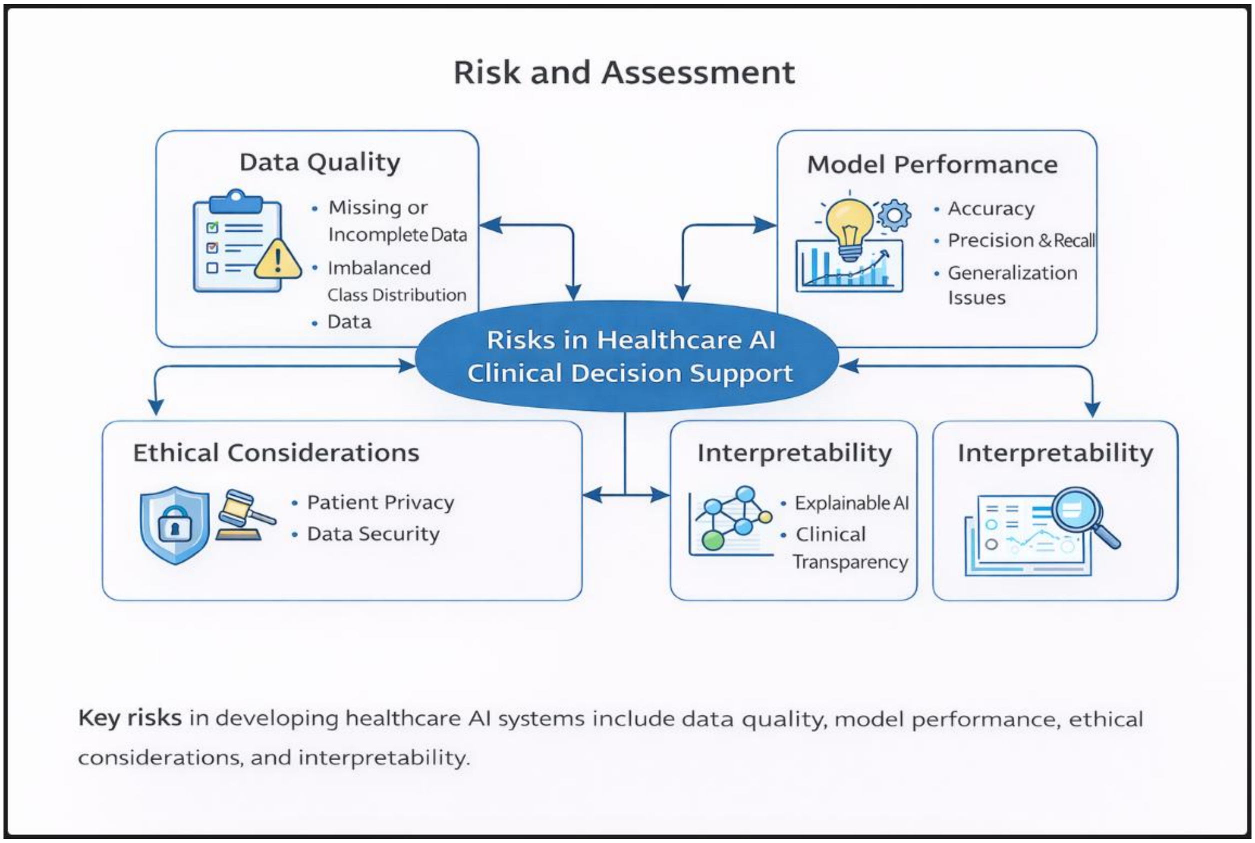


Figure 7: This figure demonstrates Comparative model evaluation metrics that reflect the accuracy, precision, recall and F1-score performance

Figure 7 demonstrates how the predictive model has performed comparatively based on four significant evaluation measures that include the F1-score, recall, precision, and the accuracy. The metrics are common in machine learning and healthcare analytics to assess the prediction effectiveness of a classification model on the outcomes of complex clinical data. The bar chart shows clearly that the model attains the highest accuracy of about 0.94. This high accuracy implies that most predictions of the model are accurate, and this implies that the model is effective in the capability of separating the outcome classes of the dataset. The value of precision is high too; it is close to 0.88, that is, when the model predicts the positive case, most of the contended predictions are accurate [22]. Precision in particular is important in clinical work due to its high accuracy since a false positive prediction is minimized thereby avoiding unnecessary treatments or medical procedures. F1-score is the harmonic mean of the precision and recall that is about 0.40, which shows a medium balance of both the precision and its capability to detect actual positive cases in the model. The recall value is however relatively smaller and is approximately 0.26 indicating that the model identifies only a fraction of the real positive cases found in the data. Reduced recall could suggest that the model is not identifying some high-risk patients. In healthcare prediction, recall is an important enhancement, as a critical case may be overlooked which will adversely affect the patient outcomes [23]. The figure indicates that the predictive model works well in terms of accuracy and precision, though more optimization methods might be necessary to enhance the recall and provide more balanced evaluation metrics in the clinical decision support system.

VII. Risk and Assessment

The process of risk assessment is a crucial part of the creation of artificial intelligence systems in the healthcare sector because it allows highlighting the possible issues that can compromise the quality and efficacy of predictive schemes. In this study, a number of risks associated with data quality, model performance, and ethical factors were put under proper consideration to make sure the Knowledge Graph-Enhanced Artificial Intelligence framework of clinical decision support is successfully implemented [51]. The quality and completeness of the healthcare data are one of the greatest risks because medical data can be missing, inconsistent, or imbalanced in the proportions of classes and affect the machine learning model performance. To overcome this problem, the data preprocessing methods, including missing values imputation, categorical encoding, and data normalization, were used in order to improve the quality of the data and assure the accurate analysis [52]. The other possible risk is associated with the predictive performance and the ability of the machine learning model to generalize [53]. The results of statistical models trained on previous data might not be consistent when using the statistical models on newer data related to the patients. To mitigate this risk, several evaluation metrics were applied such as accuracy, precision, recall, F1-score, and ROC curve analysis to carefully evaluate the model performance and determine potential limitations. Also, privacy and ethical considerations of health data are also significant risks in the area of clinical research [54]. Albeit the dataset of the present research is anonymized, patient confidentiality and proper data handling procedures are also the key aspect to ensure that the sensitive data cannot be obtained by unauthorized individuals or misused [55]. The interpretability of artificial intelligence models in clinical practice is associated with the risk since healthcare practitioners need clear and understandable systems to facilitate their decision-making. The use of knowledge graphs in the study can help in this dilemma by modeling the relationship between clinical entities and enhancing the explanations of the predictions obtained by the proposed AI-based clinical decision support system and limiting the risks that the data analysis and model implementation may bring to the clinical decision-making process.



This diagram shows critical risks and evaluation variables of healthcare AI decision systems

The Risk and Assessment diagram depicts the critical risks related to the use of artificial intelligence systems in the field of healthcare clinical decision support. The diagram provides risks in healthcare AI systems at the center with significant risk categories. These are data quality threats like missing or incomplete data, imbalanced distribution of classes, and this can impact on the model accuracy [56]. The model performance risks involve the problem pertaining to the accuracy, precision, recall, and generalization of predictive models. Ethical factors focus on patient privacy and security of data when dealing with medical information. Lastly, interpretability brings up the necessity of explainable AI and transparent clinical predictions to make healthcare professionals familiar and trustful with the AI system.

VIII. Future Work

The future of this study is to refine the proposed Knowledge Graph-Enhanced Artificial Intelligence framework to expand its predictive capabilities and its usefulness in actual health care conditions [57]. The possible avenue of future research is the incorporation of more clinical datasets to make the healthcare information more diverse and richer to analyze. Integrating several sources of healthcare information, including electronic health records, laboratory reports, medical imaging data, and clinical notes can assist in generating a broader dataset, which will reflect a broader scope of patient conditions and treatment interactions. The other significant area to work on in the future is the advancement of the machine learning models that are applied in prediction. Although this paper uses the Support Vector Machine (SVM) algorithm, predicting mortality, future studies might consider advanced machine learning and deep learning models, including the use of Random Forest, Gradient Boosting, Artificial Neural Networks, and Graph Neural Networks. Such advanced algorithms can offer better predictive accuracy and better represent any sophisticated relationships in healthcare data. Also, the interpretability and reasoning of the clinical decision support system can be further improved by further development of the knowledge graph component [58]. Future research might be concerned with covering the knowledge graph with a range of medical ontologies and domain-specific knowledge bases that model the connections between diseases, symptoms, treatments, and medications. This would allow the system to make more advanced reasoning and offer more substantive explanations to predictions [59]. The other significant direction of the future research is to help resolve the problem of class imbalance that is quite often present in healthcare data. The following techniques could be considered to enhance the detection of minority classes: data resampling, synthetic data generation, and cost-sensitive learning, which can be applied especially in the scenario with mortality prediction when the count of death cases can be rather low. Additionally, it is possible that the proposed framework could be adopted in hospitals to assist in the provision of clinical decisions in the future by studying how the proposed framework can be implemented in real-time. Having the system integrated with the hospital information systems and electronic health record platforms would enable healthcare professionals to get timely predictive information when attending to the patient [60]. Lastly, additional future research can also be used to examine the creation of easy-to-use interfaces and visualization systems that would enable clinicians to effortlessly examine model forecasts and comprehend the relationships that exist among the concepts embodied in the knowledge graph. The advancements would help to build more reliable, interpretable, and scalable artificial intelligence systems that can be used to support intelligent healthcare decisions.

IX. Conclusion

This study describes a Knowledge Graph-Enhanced Artificial Intelligence system that can assist in making intelligent clinical decisions based on ICU patient data. The analysis has considered the MIMIC3C aggregated data that serves as useful information regarding patient demographics, hospital admission traits, and clinical interactions throughout the ICU hospitalizations. Through this type of data and analysis, the study was set to create a predictive system that would detect trends based on patient outcomes and assist health workers in their informed clinical decisions. The research was conducted in a systematic methodology which consisted of data preprocessing, exploratory data analysis, knowledge graph building, and machine learning model building and performance assessment. Exploratory analysis offered some valuable knowledge on patient demographics, admission patterns and length of stay at the hospital which aided in grasping the underlying structure of the data. To boost predictability of the prediction system, the knowledge graph representation was proposed to represent relationships between clinical entities (patients, diagnoses, type of admission, and interaction with treatment) and improve the interpretation of the predictive system. On the basis of the extracted features, a Support Vector Machine (SVM) model was subsequently created to classify patient outcomes. The model was tested in terms of the traditional measures such as the accuracy, precision, recall, F1-score, confusion matrix, and ROC curve analysis. The findings made it possible to conclude that the proposed model delivers high predictive results, especially accuracy and precision, which means that it is capable of analyzing the data available about patients in the ICU and can determine the possible patterns of the outcomes. Knowledge graphs usage, enhanced by the technique of artificial intelligence, is further advantageous in that it embodies the complicated clinical links and enhances the elucidation of the prediction findings. This attribute is especially significant in medical settings wherein professionals in the medical field need clear and dependable decision support applications. Despite the positive findings of the study, some issues like data limitations, imbalance in classes, and model generalization should be considered in the future work to help come up with intelligent and interpretable clinical decision support systems. These systems may help healthcare providers to detect high-risk patients, enhance planning of their treatment, and overall improve the quality of healthcare delivery with the help of the data-driven insights.

X. References

[1]. Bhatt, S., Sheth, A., Shalin, V., & Zhao, J. (2020). Knowledge graph semantic enhancement of input data for improving AI. IEEE Internet Computing, 24(2), 66-72.

[2]. Sahlab, N., Kamm, S., Müller, T., Jazdi, N., & Weyrich, M. (2021, May). Knowledge graphs as enhancers of intelligent digital twins. In 2021 4th IEEE international conference on industrial cyber-physical systems (ICPS) (pp. 19-24). IEEE.

[3]. Liu, W., Yin, L., Wang, C., Liu, F., & Ni, Z. (2021). Multitask healthcare management recommendation system leveraging knowledge graph. Journal of healthcare engineering, 2021(1), 1233483.

[4]. Liu, Y., Ding, J., & Li, Y. (2021). Knowledge-driven site selection via urban knowledge graph. arXiv preprint arXiv:2111.00787.

[5]. Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. Complex & intelligent systems, 7(1), 439-457.

[6]. Ji, S., Pan, S., Cambria, E., Marttinen, P., & Yu, P. S. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE transactions on neural networks and learning systems, 33(2), 494-514.

[7]. Mezni, H., Benslimane, D., & Bellatreche, L. (2021). Context-aware service recommendation based on knowledge graph embedding. IEEE Transactions on Knowledge and Data Engineering, 34(11), 5225-5238.

[8]. Zi-Yun, R., Yi, Z., Jun-Tao, L., & Wan-Hua, C. (2021). Recommendation methods and systems using knowledge graph. Acta Automatica Sinica, 47(9), 2061-2077.

[9]. Lin, Y., Wang, H., Chen, J., Wang, T., Liu, Y., Ji, H., ... & Natarajan, P. (2021, August). Personalized entity resolution with dynamic heterogeneous KnowledgeGraph representations. In Proceedings of The 4th Workshop on e-Commerce and NLP (pp. 38-48).

[10]. Voit, M. M., & Paulheim, H. (2021). Bias in Knowledge Graphs--an Empirical Study with Movie Recommendation and Different Language Editions of DBpedia. arXiv preprint arXiv:2105.00674.

[11]. Lin, X., Li, Y., Xu, Y., Guo, W., He, W., Zhang, H., ... & Miao, C. (2021, December). Personalized clinical pathway recommendation via attention based pre-training. In 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 980-987). IEEE.

[12]. Dai, W., Sheni, S., & Hei, T. (2019, October). 3Q: A 3-Layer Semantic Analysis Model for Question Suite Reduction. In International Conference on Intelligent Science and Big Data Engineering (pp. 219-231). Cham: Springer International Publishing.

[13]. Lan, Q., Wen, D., Zhang, Z., Zeng, Q., Chen, X., Popovski, P., & Huang, K. (2021). What is semantic communication? A view on conveying meaning in the era of machine intelligence. Journal of Communications and Information Networks, 6(4), 336-371.

[14]. Xu, Y., Fang, M., Chen, L., Xu, G., Du, Y., & Zhang, C. (2021). Reinforcement learning with multiple relational attention for solving vehicle routing problems. IEEE transactions on cybernetics, 52(10), 11107-11120.

[15]. Li, X., Wang, Y., Wang, D., Yuan, W., Peng, D., & Mei, Q. (2019). Improving rare disease classification using imperfect knowledge graph. BMC Medical Informatics and Decision Making, 19(Suppl 5), 238.

[16]. Ceci, M., Hollmén, J., Todorovski, L., Vens, C., & Džeroski, S. (Eds.). (2017). Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2017, Skopje, Macedonia, September 18–22, 2017, Proceedings, Part II. Springer.

[17]. Krinkin, K., Vodyaho, A., Kulikov, I., & Zhukova, N. (2021). Method of multilevel adaptive synthesis of monitoring object knowledge graphs. Applied Sciences, 11(14), 6251.

[18]. Norouzi, M. (2018). Embedding Text in Hyperbolic Spaces. arXiv (Cornell University).

[19]. Wen, G., Wang, K., Li, H., Huang, Y., & Zhang, S. (2021). Recommending prescription via tongue image to assist clinician. Multimedia Tools and Applications, 80(9), 14283-14304.

[20]. Salatino, A. A., Thanapalasingam, T., Mannocci, A., Birukou, A., Osborne, F., & Motta, E. (2020). The computer science ontology: A comprehensive automatically-generated taxonomy of research areas. Data Intelligence, 2(3), 379-416.

[21]. Tan, Y., & Shi, Y. (Eds.). (2021). Advances in Swarm Intelligence: 12th International Conference, ICSI 2021, Qingdao, China, July 17–21, 2021, Proceedings, Part I. Springer Nature.

[22]. Qin, J. (2020). Research progress of news recommendation methods. arXiv preprint arXiv:2012.02360.

[23]. Yang, C., Liu, Y., & Yin, C. (2021). Recent advances in intelligent source code generation: A survey on natural language based studies. Entropy, 23(9), 1174.

[24]. Huang, B., Bi, Y., Wu, Z., Wang, J., & Xiao, J. (2020). Uber-gnn: A user-based embeddings recommendation based on graph neural networks. arXiv preprint arXiv:2008.02546.

[25]. Brabra, H., Báez, M., Benatallah, B., Gaaloul, W., Bouguelia, S., & Zamanirad, S. (2021). Dialogue management in conversational systems: a review of approaches, challenges, and opportunities. IEEE Transactions on Cognitive and Developmental Systems, 14(3), 783-798.

[26]. Sheth, A., Padhee, S., & Gyrard, A. (2019). Knowledge graphs and knowledge networks: the story in brief. IEEE Internet Computing, 23(4), 67-75.

[27]. Dai, Y., Yu, H., Jiang, Y., Tang, C., Li, Y., & Sun, J. (2020). A survey on dialog management: Recent advances and challenges. arXiv preprint arXiv:2005.02233.

[28]. Föhl, A. (2018). Media-enhanced cooking using a hands-free device (Doctoral dissertation, Stuttgart Media University).

[29]. Bai, X., Chen, Y., Song, L., & Zhang, Y. (2021, August). Semantic representation for dialogue modeling. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers) (pp. 4430-4445).

[30]. Benaich, N., & Hogarth, I. (2020). State of AI report. London, UK.[Google Scholar].

[31]. Farkaš, I., Masulli, P., Otte, S., & Wermter, S. (Eds.). (2021). Artificial Neural Networks and Machine Learning–ICANN 2021: 30th International Conference on Artificial Neural Networks, Bratislava, Slovakia, September 14–17, 2021, Proceedings, Part I. Springer Nature.

[32]. Wang, X., Zhang, Y., Wang, X., & Chen, J. (2019, April). A knowledge graph enhanced topic modeling approach for herb recommendation. In International conference on database systems for advanced applications (pp. 709-724). Cham: Springer International Publishing.

[33]. Zong, C., Xia, F., Li, W., & Navigli, R. (2021, August). Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural

language processing (volume 1: Long papers). In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers).

[34]. Xie, X., Styles, I., Powathil, G., & Ceccarelli, M. (2018). Artificial intelligence in healthcare.

[35]. Li, Z. (2021). Improving Recommender Systems via Multimodal Information. University of California, Los Angeles.

[36]. Shao, W., Chen, X., Zhao, J., Xia, L., & Yin, D. (2021). User behavior understanding in real world settings. arXiv preprint arXiv:2112.02812.

[37]. Jurafsky, D., Chai, J., Schluter, N., & Tetreault, J. (2020, July). Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics.

[38]. Espinoza-Mejía, M., Saquicela, V., & Abril-Ulloa, V. (2020, October). Ensuring traceability and orchestration in the food supply chain. In XV Multidisciplinary International Congress on Science and Technology (pp. 135-149). Cham: Springer International Publishing.

[39]. Chen, J., Liu, L., Chen, R., Peng, W., & Huang, X. (2021). SecRec: A privacy-preserving method for the context-aware recommendation system. IEEE Transactions on Dependable and Secure Computing, 19(5), 3168-3182.

[40]. Beebe, N. H. (2021). A Complete Bibliography of Publications in Future Internet.

[41]. Wang, C., Liang, S., Jin, Y., Wang, Y., Zhu, X., & Zhang, Y. (2020, December). SemEval-2020 task 4: Commonsense validation and explanation. In Proceedings of the Fourteenth Workshop on Semantic Evaluation (pp. 307-321).

[42]. Burkett, Z. D. (2017). Network-based Insights to Learned Vocalization. University of California, Los Angeles.

[43]. Shao, W., Chen, X., Zhao, J., Xia, L., & Yin, D. (2021). Sequential Recommendation with Adaptive Preference Disentanglement. CoRR.

[44]. Haick, H., & Tang, N. (2021). Artificial intelligence in medical sensors for clinical decisions. ACS nano, 15(3), 3557-3567.

[45]. Garcia-Vidal, C., Sanjuan, G., Puerta-Alcalde, P., Moreno-García, E., & Soriano, A. (2019). Artificial intelligence to support clinical decision-making processes. EBioMedicine, 46, 27-29.

[46]. Buchlak, Q. D., Esmaili, N., Leveque, J. C., Farrokhi, F., Bennett, C., Piccardi, M., & Sethi, R. K. (2020). Machine learning applications to clinical decision support in neurosurgery: an artificial intelligence augmented systematic review. Neurosurgical review, 43(5), 1235-1253.

[47]. Musen, M. A., Middleton, B., & Greenes, R. A. (2021). Clinical decision-support systems. In Biomedical informatics: computer applications in health care and biomedicine (pp. 795-840). Cham: Springer International Publishing.

[48]. Loftus, T. J., Tighe, P. J., Filiberto, A. C., Efron, P. A., Brakenridge, S. C., Mohr, A. M., ... & Bihorac, A. (2020). Artificial intelligence and surgical decision-making. JAMA surgery, 155(2), 148-158.

[49]. Tyler, N. S., Mosquera-Lopez, C. M., Wilson, L. M., Dodier, R. H., Branigan, D. L., Gabo, V. B., ... & Jacobs, P. G. (2020). An artificial intelligence decision support system for the management of type 1 diabetes. Nature metabolism, 2(7), 612-619.

[50]. Abdel-Basset, M., Manogaran, G., Gamal, A., & Chang, V. (2019). A novel intelligent medical decision support model based on soft computing and IoT. IEEE internet of things journal, 7(5), 4160-4170.

Peiffer-Smadja, N., Rawson, T. M., Ahmad, R., Buchard, A., Georgiou, P., Lescure, F. X., ... & Holmes, A. [51]. H. (2020). Machine learning for clinical decision support in infectious diseases: a narrative review of current applications. Clinical Microbiology and Infection, 26(5), 584-595.

Antoniadi, A. M., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B. A., & Mooney, C. (2021). Current [52]. challenges and future opportunities for XAI in machine learning-based clinical decision support systems: a systematic review. Applied Sciences, 11(11), 5088.

[53]. Khanagar, S. B., Al-Ehaideb, A., Vishwanathaiah, S., Maganur, P. C., Patil, S., Naik, S., ... & Sarode, S. S. (2021). Scope and performance of artificial intelligence technology in orthodontic diagnosis, treatment planning, and clinical decision-making-a systematic review. Journal of dental sciences, 16(1), 482-492.

[54]. Lee, M. H., Siewiorek, D. P., Smailagic, A., Bernardino, A., & Bermúdez i Badia, S. B. (2021, May). A human-ai collaborative approach for clinical decision making on rehabilitation assessment. In Proceedings of the 2021 CHI conference on human factors in computing systems (pp. 1-14).

[55]. Haleem, A., Javaid, M., & Khan, I. H. (2019). Current status and applications of Artificial Intelligence (AI) in medical field: An overview. Current Medicine Research and Practice, 9(6), 231-237.

[56]. Schoonderwoerd, T. A., Jorritsma, W., Neerincx, M. A., & Van Den Bosch, K. (2021). Human-centered XAI: Developing design patterns for explanations of clinical decision support systems. International Journal of Human-Computer Studies, 154, 102684.

[57]. Tack, C. (2019). Artificial intelligence and machine learning| applications in musculoskeletal physiotherapy. Musculoskeletal Science and Practice, 39, 164-169.

[58]. Adlung, L., Cohen, Y., Mor, U., & Elinav, E. (2021). Machine learning in clinical decision making. Med, 2(6), 642-665.

[58]. Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: focus on clinicians. Journal of medical Internet research, 22(6), e15154.

[59]. Andronie, M., Lăzăroiu, G., Iatagan, M., Uță, C., Ștefănescu, R., & Cocoșatu, M. (2021). Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. Electronics, 10(20), 2497.

[60]. Safdar, S., Zafar, S., Zafar, N., & Khan, N. F. (2018). Machine learning based decision support systems (DSS) for heart disease diagnosis: a review. Artificial Intelligence Review, 50(4), 597-623.

[61]. Dataset Link:
https://www.kaggle.com/datasets/drscarlat/mimic3c