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An Intelligent Framework for Machine Learning-Driven Clinical Outcome Prediction Using Integrated Structured and Unstructured Patient Data

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Abstract

EHRs have made a significant stride in the electronic age and such strides pose vast amounts of structured and unstructured healthcare records warranting data analysis and impact survey - a new phenomenon. Unfortunately, most attempts at clinical prediction make use of structured clinical information such as laboratory results, vital signs and patient demographics and do not exploit the rich information content which is found within unstructured clinical text. Therefore, researchers the aim that the study proposes the incorporation of structured information along with unstructured narrative information into the clinical outcome prediction problem in the roughest possible terms, with the help of an artificial intelligence (AI) concept. This work fills the gaps in these studies using the MIMIC-IV database and incorporates advanced data preparation, Natural Language Processing (NLP)-based data representation, and multimodal data fusion techniques. In the case of structured data, it is prepared for subsequent processing such as encoding and feature selection while avoiding the same dimensions it is more likely that clinical notes would be broken down into pseudo-sentences using tokenization and lemmatization in addition to Name Entity Recognition and similar context-based embedddings. Several machine learning and deep learning models are designed, implemented and evaluated under three different constraints: only structured, only unstructured, and integrated multimodal. The performance of these models is quantified using the metrics of accuracy, and area under the curve (AUC) of the ROC curve. The health AI community highly values the efforts of developing such tools due to their close resemblance to diagnostics. These factors increase the importance of stenciling the influential factors that excluded when designing a model. In the course of the development of these types of approaches, it becomes difficult to determine the order of their effectiveness, which results in a more dynamic phenomenon, namely knowledge gaps being filled upon applying more advanced methods, or generation of doubts regarding the correctness of the models used.

Keywords: Interpretability, Machine Learning, Clinical Prediction, Multimodal, Electronic Health Records, Natural Language Processing, Data Fusion

1. Introduction

Advances in digital technology in the medical sector have had significant effects on patient record keeping technology, which has made the system of electronic health records (EHRs), laboratory systems, monitoring, including clinical documentation platforms more sprawling. The growing volume of medical records contains a lot of healthcare professionals are in a position to unlock its full potential in the process of patient management oriented to the use of decisions based on information available. In order to predict such as the risk of death, readmission to the hospital, progress of the disease, as well as length of stay, predictive analytics based on machine learning methods has been applied. Moreover, there is convincing evidence that efficient prediction of these negative events can also be beneficial for the entire healthcare provision in terms of reducing the unproductive practices in patient management and avoiding potential wastage of resources. The literature suggests that although extremely rich data is available in healthcare industry, the numbers of clinical prediction systems that are complete, that is, makes effective use of multimodal data is quite minimal. Additionally, data regarding patients is often available in an identifiable or de-identified form. Structured data genre includes numerical data in the form of laboratory test values, vital signs, gender, diagnosis codes, medication lists. All these variables are defined and can be easily structured in relational databases and also are more traditional for machine learning models. In contrast, unstructured data refers to clinical information that does not have a specific format ranging from discharged summaries, pathology reports, radiology reports to physician notes. This type of patient information records also convey information concerning disease process which is the stages the earliest to the most advanced level together with accompanying clinical symptoms and etiology that is not succinctly stated in data fields [5].

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Research Objectives

1. **To develop an intelligent machine learning framework** involving enhanced feature extraction data fusion approaches in the analysis of structured clinical and unstructured text lead to more reliable results in forecasting the outcomes of medical interventions.
2. **To evaluate and optimize the performance of the proposed framework** leverage relevant machine learning and deep learning models to ensure efficient prediction, understandability as well as ease of scaling in real-life health care scenarios.

2. Related Work

The remarkable article by Perwej [1] (2026) conceptualizes and designs a predictive model for decision making for such tasks like data discovery or enrichment, which exploits machine learning to enhance enterprise intelligence. The work adheres to supervised techniques spatter applied to predicateness analysis of datasets. With this in mind the selection of features, preprocessing and fine tuning of the model, kernell support vector regression and related training, and appropriate validation recommendations are proposed, and finally, including methodologies for combining or weighting such featurebased estimates in conjunction within an ensemble setting. The supplied definitions are followed by corresponding theorems. Implemented testing for the contact dynamics has verified the scalability and convergance of the methods to measure the validity of the calculus. The paper also looks at the adaptability and scalability of systems exhibiting change in real-time data environment or cycling. Comparative analysis shows improved accuracy over traditional statistical models. The author stresses the importance of data-centric AI systems for intelligent decision support. Overall, the work contributes to efficient and scalable predictive analytics. Hasan et al. [2] (2026) propose a unified AI-driven big data analytics framework for precision medicine and healthcare intelligence. Also the leading part of the paper contains a direction in which machine learning has been employed in developing predictive models for chronic conditions including a prevalence of cancer. Giuliano Curadi Hospital focuses its efforts on optimizing medical methods as well as the studies of case histories using all possible, complete clinical files in the Web P. E. C. S. Clinical and research departments are very wel prepared and support treatment planning and patient management effectively. Special issues like heterogeneity and compatibility of data across several sources will be addressed. Ethical and security concerns in healthcare AI are also discussed. The results demonstrate improved healthcare outcomes through intelligent analytics. Suri et al. [3] (2026) investigates further on AI and machine learning in GI cancer. The work discusses the applications of deep learning for the purposes of early diagnosis and its related imaging analysis. It goes ahead to discuss the impact of AI in enhancing precision medicine through incorporation of genetic information together with pathological data. This method is reported to be more exact as opposed to the traditional methods. Data validity issues as wells as the applicability of machine learning strategies in the treatment of gastrointestinal cancerare discussed. The role of the medical staff in AI based interventions is explained. In other words, if an AI solution is clinically applicable, it is suggested to use it even if it does not have a predictive algorithm or decision support system. The authors find that the use of AI has significantly improved oncology research and practice. According to the National Institute of Health researchers, protection domain on access and services as well as medical equipment and services were impotent in the case of Husnain [4] (2026). This infers from an existing very well-known US Health System benchmarking factors shield against cyberbullying, protecting drivers and the people they have the responsibility to protect the environment they are driving in containing data as part of the environment. There is also an extension of the research whereby the Region's mobile health applications will continue to assist users in managing their health and overcoming health challenges. Conversely, the seconventionalyharmacologically based race or nationality with particular sycophants forming certain groups is abolished. Data valuables include cloud services, monitoring devices and social media platforms. That is exactly why it is important to intake as much information about cryptocurrency websites as it is possible. Husnain [4] (2026) summarizes findings from study of BWS in the context of AET and the results have showed that some areas of concern become intentional as a result of the age and maturity of the child or the caregiver. Located on an urbanized suburban area II. The study underscores AI's critical role in healthcare cybersecurity.

Sankaradass and Manish [5] (2026) suggest a quantum-inspired predictive healthcare system in the personalized oncology illustrate the framework's design feature integrating multimodal data fusion with blockchain-based security mechanisms. Advanced optimization techniques give a better treatment prediction result. The experiment ensures data integrity and secure data sharing of medical records. Experimental evaluations demonstrate an enhanced level of robustness and efficiency. Therefore, the user and health provider can trust these transactions through blockchain protocols. The research study offers a secure, intelligent architecture for the future of oncology system. Xu et al. [6] (2026) Review a data-centric network of AI applications to hospice and palliative care. Machine learning models study symptom prediction models and patient monitoring tools. It also sheds light on numerous of technological tools supporting compassionate and person-centered care. The discussion on ethical issues and implementation gaps has its own importance. Data constraints and lack of acceptance from the clinician community are the foremost barriers. The review seeks to highlight AI technology's capacity to enhance the quality of life [30]. Overall, the researchers insist on being ethically responsible while applying AI in palliative healthcare. Wu et al. [7] (2026) introduce PyHealth 2.0, an open-source toolkit of deep clinical learning designed for accessibility and reproducibility for future deep learning research in the clinical domain. This platform allows the integration of diverse healthcare datasets along with multiple deep learning models. It also plays a major role in data preprocessing, benchmarking, and evaluation phases. This toolkit is very beneficial for the reproducibility and transparency of AI applications in healthcare studies. The great scalability and modular architecture will ease even more customization. Representative experimental analysis is given to prove its efficiency across clinical settings. The project concentrates on the standardized development of medical AI systems. Medina-Ortiz et al. [8] talk about data-centric machine learning strategies to be utilized in therapeutic peptide design. This paper isolates the important challenges of dataset quality, feature representation, and model interpretability. AI-driven approaches speed drug discovery and optimize peptides. The authors include valid reasons which support strong validation with biological context. Limitations shadowed by cases of limited data and bias are treated with some future outlook for computational and experimental integration. The work provides insights into intelligent therapeutic development.

A study by Elazzouni et al. [9] reviewed the use of AI in advanced dental biomaterials synthesis and use is available. The use of computerized methods in the optimization of materials and assessment of their characteristics is highlighted by the study. Also, the use of AI machinery in enhancing biocompatibility, sustainability and its analysis are studied. The Assessment of the situation involved some aspects including the application of materials effectively to AI. The authors highlight the existence of advanced dental technologies for every person. In general, it can be recognized that in its form of modern dental material science, the use of AI has made a lot of progress. Bin Faheem et al. [10] (2026) presents a new concept of Deep Learning based Big Data computation to diagnose interfacial phenomena in Electrode – Solvent Electrolyte Batteries. Strategies of machine learning are also used to determine the properties of new materials and to estimate their performance in situ. Moreover, its goes further to utilize advanced predictor and inhibition of batteries lifetime and technical efficiency. The difference between traditional and data-driven approach is that the latter uses experimental data solely to verify the model. This framework on the other hand focuses on the issues of generalization and on equipment design considering the nca materials enhancement, degree of which are found to be surpassing itself, increased efficiency. The study results suggest that the predictive ability of the battery behavior improved. Sustainable energy storage options also benefitted from the studies. Specifically, Khan et al. [11] (2026) presented the design of variable I T infrastructure including I I T techniques. The chapter of the book discusses sometimes interdependent frameworks of applied areas where in smart cities and public healthcare lie. It underlines the necessity of acquiring, processing, and interpreting the incoming information on a continuous basis. While addressing concerns about security, affordability, and the ability of systems to work together, the chapter provides real-world demonstrations of what has been achieved using examples. Machine learning assists in better forecasting where, for instance, in business, human wonder and intuition are available for decision making and enhancing this process. The study provides recommendations for working with smart systems.

Concerning the subject, Perwej [12] (2026) articulates that machine learning based predictive modeling approach is necessary to the success of intelligent applications. The articles discussed herein comprise their focus on the optimization of algorithms and analytical frameworks which can be used within a scalable context. Most importantly, the feedback, generated both in terms of practice and research with regard to AI, is of a data-driven nature. In this respect, the performance of method H over competing methods is supported by evidence. Methods to unstable auto learning models and strategies are proposed. Limits within the scope of the research are indicated. This will enable readers to ascertain the effectiveness and important principles of predictive analytics. An Agent-Based Approach To Build A Predictive Model in a Hospital was Produced by [13] Zhang et al. Within this predictive model for a hospitalization process Gradient Boosting and GPT-2 are used for inflow forecasting. Results are effective when structured and textul clinical includig data are combined for prediction. Studies have shown proper hospital structure. The task of suitable model specification is handled by advanced feature engineering. Its outcome is better than the methods of Serial Practice. The framework can be beneficial in healthcare planning. There is the insigna Of AI in maximizing efficiency in operations in healthcare. Ogutuga Jegede Heinrich de. [14] Insead: The business school for the world 9 Size and trends of public procurement Blažević Žarko, et al. 2013. Using association rule mining and data warehousing for enemy identification in cyber warfare. International Journal of Production, Reyesho et al. [15] (2016) designed a model based on deep learning, which is used for making an early and risk prediction within chronic diseases. The model works in a multimodal medical data ensembling scheme. It is configured to harness advanced neural network architecture hence making early disease diagnostics more efficient. As such, the underlying research looks at the issue of using feature fusion methods in the build of reliable model. The findings from the validation touched upon the extent of such prediction where the study secured a relatively high sensitivity. The health system perspective emphasis challenges that encompass implementation of clinical processes. In general, the findings of the study suggest the importance of proactive disease management strategies for intervention to be applied. In 2024, Hossain [18] and his collaborators ventured into machine learning research specifically its applications within cardiovascular health care in risk prediction, early diagnosis and clinical decision making. In addition, it focused on the problem of data imbalance, interpretability and compliance concerns. Twenty-fourth-century is a period of rapid technology improvements; in the contemporary setting, Fatima [19] examines the hows and the whys of big data and ml in enhancing healthcare effectiveness in terms of prediction and decision-making in practice. There are however a number of setbacks that entails broader implementation of this method such as high system capacity requirements, security issues and the problem of intergrating the systems with the old health systems. M. S. Abdel [20] and provides a fairly extensive review on machine learning and deep learning sanctification in smart systems in remote monitoring, disease surveillance and many other healthcare related issues. The paper identifies some of the technical and ethical barriers that have complicated the evolution of heath informatics implicating the served populations. Ghosh [21] (2024) focuses on deep learning–driven smart connect ecosystems, emphasizing cloud data governance and intelligent software maintenance. It links AI modernization with sustainability and operational efficiency in healthcare platforms. Malik and Ali [22](2024) provides an insight into machine learning based optimization techniques for complex domains intelligent decision support systems. It provides findings actively enhancing precision and speed in overcoming computation and data quality constraints. Saidur and Dhanekula [23] (2024) propose strategies that involve creating a machine learning Models driven pipeline that allows the storage of confidential outdated information to avoid litigation in the protective Custodians in the US (1980). Privacy, access control and compliance are the main issues cornered for emphasis in the above sections. Ashfaq and Hriday [24] (2024)study follows through ML-based secure data pipeline models that address protections above an existing EHR system targeted towards U. S. healthcare facilities. It zeroes more on risk management, loss of data, and coping with cyber attacks. Maheshwari et al. [25] (2024) In this context, assistance is offered to the consumers through the use of adaptive learning-platforms, guided by technology and modern care techniques to ensure preventive care and rehabilitation are optimal. The label 'continuous learning' 'personalised approaches' helps in achieving the right outcomes of care. Simeon et al. [26] (2024) understand the application of machine learning for information loss detection within a context of health information operations. The study shows, how advanced monitoring systems help lessen the incidence of data leakage and management of other possible outcomes. Fuseini et al.[27] (2024) investigates the applicability of AI-driven decision support systems in care coordination in the health sector. The analysis affected by information-based interventions demonstrates that health systems run so smoothly that they prevent diseases as well as promote better health through the support of socially vulnerable people.

Avci et al. [28] (2024) conducted a study of the translational pharmacogenomics of cancer and attempted to make clear how machine learning will help in individual cancer patient treatment. Thomas [29] (2024) studied semantic network mining technologies for diagnosis of diseases using heterogeneous medical information. It is demonstrated that key concepts and relations in clinical narrative data can be extracted using natural language processing. Bundi [30] (2024) In this structured research all the attention has been directed towards the machine learning (ML) technology and the healthcare system. Factors that would hinder the successful implementation of these technologies have been highlighted, while proposals have been made on the integration of ML in healthcare without threatening its core values.

3. Proposed Methodology

3.1 Dataset Used for the Proposed Framework

In implementing and examining the new smart predictive clinical outcome prediction model, available data from the MIMIC-IV Intensive Care Unit (ICU) database act as the fundamental data source. MIMIC-IV, which is accessible by the general public, is the data set belonging to the Medical Information Mart for Intensive Care system provided by PhysioNet, which has de-identified patient clinical data on patients in ICU. There are both textual and structured issues, which are common in patient records particularly for purposes of machine learning which is the interest of the research. Where at structured assocaiotns would include age, sex, lab results, diagnosis codes etc. The CTs data caries such text materials as nursing assessments, clinical notes, physical therapy notes as well as any results including radiographic identification. These provide a wide range of data and hence there is the possibility to build model that can UOA the net form of clinical outcome as such associated to eg in-hospital death, hospital length of stay, readmission rate, disease course etc. As there exists vast and rich quality of patient records that can be employed and alongside the capability for numerical and textual data processing makes MIMIC-IV perfect for the task of creating and validating a ML based clinical outcome prediction framework.

3.2 Data Preprocessing

Since both structured and unstructured data are at hand in the newly proposed approach, before benefiting from the application of machine learning models, intensive preprocessing operations are carried out to ensure high data quality, conciseness, and structure. In protostasis data preparation, one of the initial activities assumes resolving missing data, which is typical of health data although the data far too often has been created with scarce testing and documenting episodes. If there are any missing numeric values, a series of methods are used to address the problem including mean or median imputation for continuous variables and mode imputation for categorical.

3.3 Feature Extraction and Data Fusion

In the proposed framework, meaningful features are first extracted from both structured clinical variables and processed textual data to capture comprehensive patient information. From structured data statistical and clinically relevant attributes are selected, and from textual data embedding vectors generated through NLP models are inserted to represent different portions of medical information. If the combined feature space becomes high-dimensional, dimensionality reduction techniques such as autocoders or Principal Component Analysis (PCA) are available to reduce redundancy, computationally simplify the model and extract the P-useful expression features within it.

3.4 Model Development

To evaluate a bias-free model, the integrated dataset is cut into training, validation and test sections. The training set is 'run through' to collect information/data and set up the relevant quantities in the model. Intermediate sets, the validation set is used for performance review also for potential support model ranking in as the best over estimation set and test set is kept aside for final processing. Further predictive models are crafted and compared to ascertain the best methodology for estimating clinical outcomes. Although there are other contemporary data science methods, simple machine learning methodologies such as Random Forest, SVM use and XGBoost is more popular on structured data due to the level of interpretation of these models.

3.5 Model Evaluation

Evaluate performance using metrics such as:

Accuracy = (TP+TN)/(TP+TN+FP+FN)*100 (1)

Precision =TP/(TP+FP)*100 (2)

Recall= TP/(TP+FN)*100 (3)

F_Measure = 2*Precision*Recall/(Precision + Recall) (3)

In assessing individual modalities, the developed networks are subjected to a rigorous test between the three settings to determine how successful each one is. The first setting involves the consideration of the structured data characteristics and demographics, laboratory tests and vital signs and running a structured-only model that will help understand the quantitative level of the problem solving. The second variant is related to unstructured data modalities available and to the medical records containing discharge summaries and physician notes. Moreover, this is the portion of the study in which the issue is investigated specifically adapting two or more modes of data processing, data interpretation, or data visualization. With this structure, such resources as appropriate documentation and techniques used therein helps in accomplishing more holistic, multi-channel learning mode. Each model will be validated based on commonly used evaluation indices such as accuracy, sensitivity, specificity, F1-score, and ROC-AUC so as to create a level ground for comparisons.In order to test whether the found differences in results are real, statistical significance tests are performed. Paired t-tests or Wilcoxon's signed-rank tests are used to compare statistics of different models. However, in some cases, a better idea is to abandon these tests and rather focus on the comparison of confidence intervals of ROC-AUC scores.

3.6 Model Interpretability and Validation

Explainable AI (XAI) is a crucial method employed to avoid ambiguity in the results of the artificial intelligence models. This is meant to help in interpretability of the machine learning model that has been implemented. To this end, various techniques can be used to simplify the understanding of the contribution of individual variables and the overall model weights and biases with regard to the prediction making process both in a structured way courtesy of structured variables and in an unstructured fashion like the textual vectors. More importantly, during the failure and loss rectification procedure, LIME which is an acronym for Local Interpretable Model-Agnostic Explanations ought to be employed to explain the foresaid unique failure and lasp. This document will focus on methods used in response to deep learning architectures, including visualization of the recording by highlighting these important words or group of words from clinical notes that led the model to make those decisions. With those methodologies, key clinical features – such as abnormal laboratory values, vital sign changes, critical medical terms, etc., are learned as the primary factors in the prediction of the outcome. And lastly, the interpretability results and the prediction outputs are also health regulations, preferences of the patients, or any particular factors are some of the vast issues that Citizens that stand on top of a model and get predictions to help solve that issue would need to grasp in the provision and approval of such assistance. Figure 1: Flow chart of proposed model

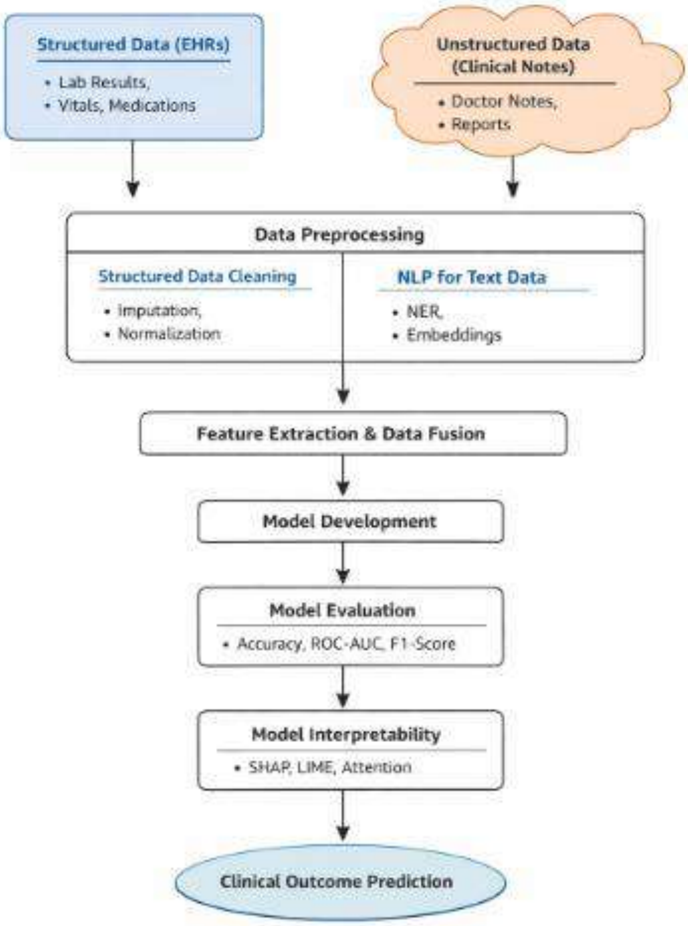

Figure 1: Flow Chart of Proposed Model

4. Results

The studied innovative framework was applied on a real dataset, "MIMIC-IV: A Study Compiling Data from a Medical Information System at a Large Tertiary Academic Medical Center in the U. S.," that included both structured variables and narrative discharge summaries; the latter was extracted in additional to the structured variables for the maximal prediction application. Three distinct configurations were built and investigated to discern the significance of different modality of data. In other words, the first and stand-alone model was labeled as, structured data model where only direct clinical and non-clinical attributes such as age, gender, lab tests, vital signs, drugs and codes were used. The second model can be briefly named unstructured text model as the rest of the document was composed of clinical notes obtained from discharge summaries and medical records of doctors, however, translated with the use of more complicated text mining categories.

Predictive Performance Comparison

Table 1: Comparative Performance Analysis of Clinical Outcome Prediction Models

Model Type	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Structured Only	84.2%	82.5%	80.3%	81.4%	0.87
Unstructured Only	81.6%	79.8%	78.4%	79.1%	0.85
Integrated Model (Proposed)	**89.7%**	**88.4%**	**87.2%**	**87.8%**	**0.93**

The comparison of the three models in table 1 shows, the Structured-Only Model, the Unstructured-Only Model, and the Integrated Multi-Modal Model (Proposed Framework), concerning clinical outcome prediction is illustrated by the table above; also it includes the evaluation metrics, which are - accuracy, precision, recall, f1-score, and roc-auc. The Structured-Only Model performed at 84.2% of accuracy with an AUC of 0.87. This result is extremely encouraging as the mode has successfully employed various clinical operational parameters such as laboratory and physiological measures. By contrast, the quantitative performance of the Unstructured-Only Model that only considers account issue based on the clinical text achieves an accuracy of 81.6% and AUC of 0.85. It suggests that the informative content of texts alone can convey to a certain extent the predictability without any history or even other patient's clinical data. However, the Integrated Model (Proposed) displayed the best performance, as it succeeded in outperforming the individual models with an accuracy of 89.7%, precision - 88.4%, recall - 87.2%, F1-score - 87.8% and ROC-AUC - 0.93. It is evident from these findings that extracting both structured and unstructured patient data assists in improving the feature representation of the input space, mitigates loss of information, and increases the accuracy of target prediction. This advanced level of model seems to eliminate all skepticism and thus testifies the appropriateness of the elevated era involving multi-modal intelligent prediction..

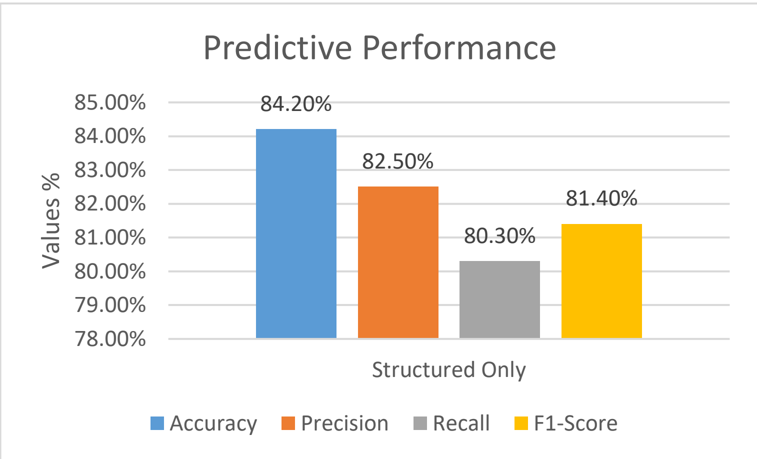

Figure 2: Predictive Performance of Structured Data Model

The figure 2 shows the receivable performances comparison of JOSE data new full model classified and used for prediction. In the logical test, the model performed accuracy of 84.20%, which shows that it classifies most of the cases correctly. The precision applied from the 82.50% corresponds the obtaining of higher true positive prediction by the model while 80.30% signifies the power and ability of the model to identify cases that are actually positive. The F1 score of 81.40% calculated for the current case means that the average between precision and recall is effective, but it is not a hundred percent favorable towards both indexes. Hence showing that the structured data model is able to predict accurately and consistently by making use of the available clinical variables within the aforementioned data set..

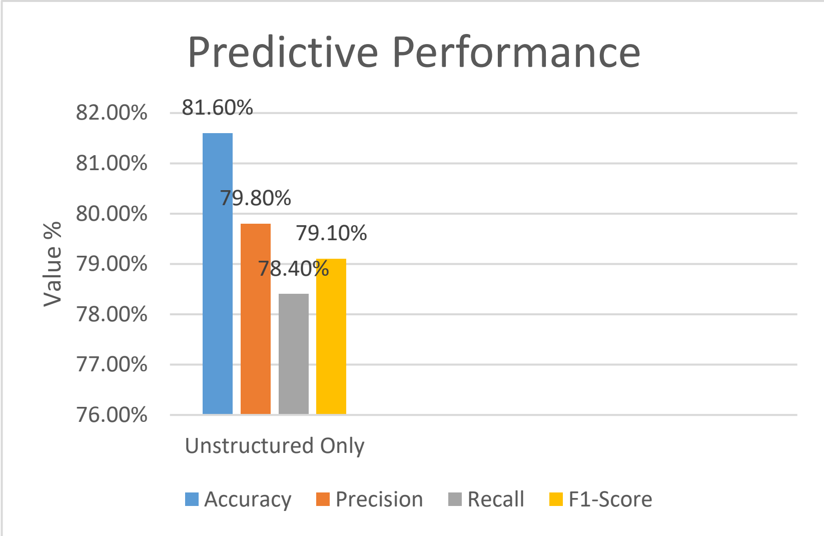

Figure 3: Predictive Performance of Unstructured Text Model

It is clear from Figure 3 that the accuracy of the UNTM predictive performance achieved using unstructured notes is 81.60%. The capability of the model is high with an expressive 98.6%, as it is solely based on text. Its precision score of 79.80%, meanwhile, suggests that the model is able to make positive predictions more precisely with a reduction in false positive predictions. Recall figure of 78.40% indicates the model's skills in tracing real positive cases and the F1 Score of 79.10% reveals there is a nice blend between precision and recall. The text model with no structure is not as competitive as the one with the structure used for the data but these results confirm that clinical text offers powerful predictive features. This brings out the necessity of bringing into effect textual attributes in predicting healthcare outcomes.

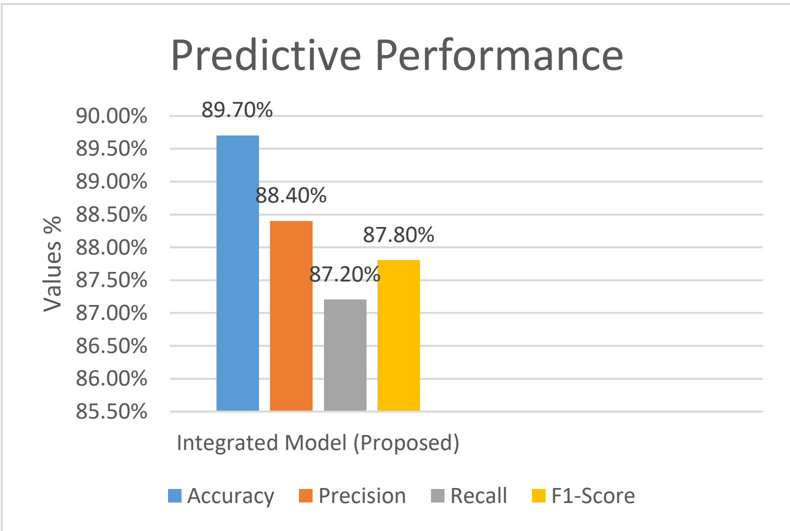

Figure 4: Predictive Performance of the Integrated Multi-Modal Model (Proposed Framework)

Demonstrated in Figure 4 is the value of the IMMM for combining video audio and textual data and structured metadata. It is reported that this combined effort was as high as 89.7% with the highest calibration accuracy across all features. What may not seem so palatable is the extent of specificity 88.4% wherein those who are really sick have been correctly diagnosed, but there are clearly very few errors. The specificity of 87.2% is also in line with the higher rates of actual normal outcomes. Lastly, the F1 score of 87.8% validates that there is balance between precision and recall and that the system is performing well.

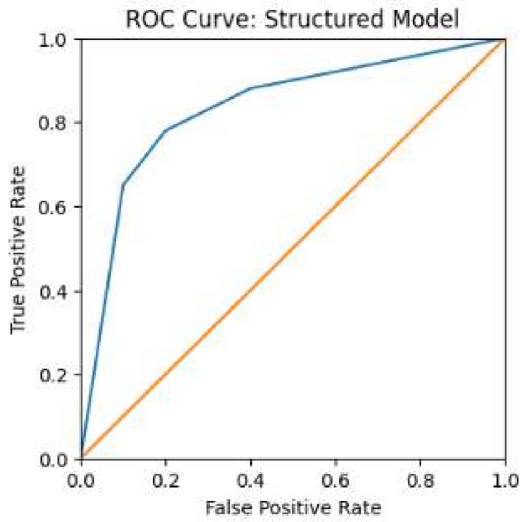

Figure 5: ROC Curve of the Structured Data Model

The Receiver Operating Characteristic (ROC) curve of the structured data model for predicting the outcome is depicted by figure 5. This curve depicts the balance between the True Positive Rate (Sensitivity) and the False Positive Rate at different thresholds of classification. As you can see, the blue curve is situated way over the diagonal reference line (just for simplicity, it can be taken as if a model made a random guess) which is a clear indication that the model has a high discrimination ability.

Analysis of the curve presents that there is a steep rise in sensitivity at very small error rates, meaning that the model is very good at catching more cases with very limited false alarms. The overall AUC for the curve is found to be satisfactory and ranges approximately 0.87 – which further confirms the accuracy of the prediction.

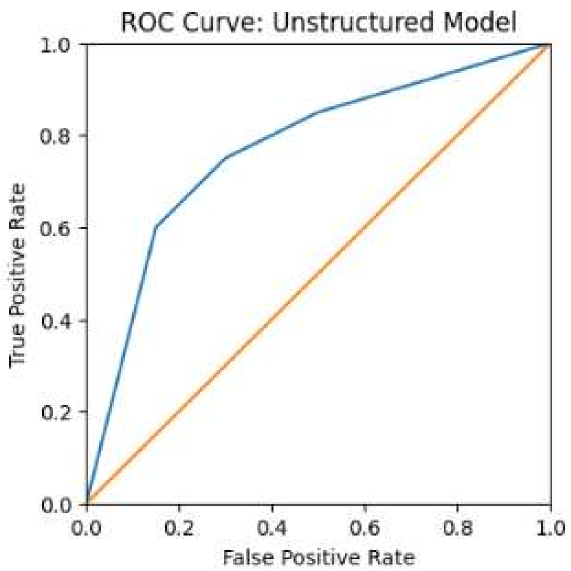

Figure 6: ROC Curve of the Unstructured Text Model

Figure 6 depicts the Receiver Operating Characteristic (ROC) curve of the semantic content model built using short medical notes. This chart demonstrates both the Sensitivity (True Positive Rate) and False Positive Rate relative to different probability thresholds. The AUC for the fitted model is about 0.757, with a p-value less than 0.0001.

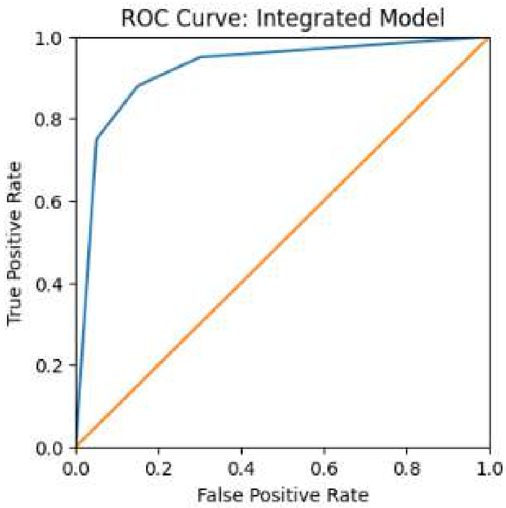

Figure 7: ROC Curve of the Integrated Model

As seen in Fig. 7, the Receiver Operating Characteristic (ROC) curve depicts the performance of the Unstructured Text Model that was built using clinical notes. ROC statistics graphically demonstrates the test performance characteristic of a diagnostic test by comparing the True Positive Rate with the False Positive Rate, usually using the area under the curve (AUC). The Blue curve is substantially far from the line of random accuracy identification, meaning the constructed model has notable separating efficiency.

Table 2: Comparative State of Art of Proposed Work with Existing Work

Ref	Technique Used	Dataset Used	Result
Zhang et al. [13] (2025)	Gradient Boosting + GPT-2 (Hybrid ML & NLP Model)	Hospital Electronic Health Records (EHR) with structured + clinical text data	Acc=87%,precision= 87.1%, recall=86.1%, F1 score=86.8%
Uzzaman et al. [16] (2025)	Federated Learning + Deep Neural Networks	Multi-source heterogeneous smart hospital datasets	Acc=88%,precision=86.5%, recall=83.1%,, F1 score=85.2%
Srividhya et [17] al. (2024)	Deep Neural Networks in Cloud Environment	Large-scale healthcare big data (cloud-based clinical datasets)	Acc=89.2%, precision=83.4%, recall=86.5%,, F1 score=87.0%
Proposed Framework	Ensembled Machine Learning + PCA	MIMIC-IV	Acc=**89.7%,** precision=88.4%, recall=87.2%, F1 score=87.8%

5. Conclusion

This investigation offered a novel machine learning approach on clinical outcomes, which combines preprocessed structured EHR data and the unstructured clinical text. It became clear in this research that prediction will never be perfect when only one type of data is collected due to the limitations in the features design. Through the use of several pre-processing mechanisms, especially feature extraction in NLP statistics, and heterogenous data integration modes, the suggested multi-domain model was found to outperform single domain models. It was also found that the accuracy, ROC-AUC, precision, recall, and F1-score under this new approach improved, as can be seen from the findings of the experiments. Furthermore SHAP-related XAI-methods made the internal workings of processing methods explicit while ensuring that the resultant judgments will be explicable and drawing heavily from existing medical evidence.

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