**Developing a Healthcare Monitoring System with a Comprehensive Dashboard**

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**1) (12)**

**Summary:** Using data from 10,000 diabetic patients, the study offers a thorough analysis of the use of machine learning in diabetes treatment. The study compares many machine learning algorithms for predicting diabetes complications, and Random Forest outperformed SVM (81.2%) and Neural Networks (79.5%) with an accuracy of 85.6%. With a sensitivity of 88% in identifying diabetic nephropathy, the Decision Tree model indicates the study's effective risk stratification and early detection capabilities.

**Main Contributions:**

* Performance Benchmarking: The study provides quantitative performance metrics for multiple machine learning algorithms in diabetic complication prediction:
  + Random Forest achieved the highest accuracy (85.6%)
  + Support Vector Machines showed 81.2% accuracy
  + Neural Networks demonstrated 79.5% accuracy
  + Gradient Boosting model achieved an impressive AUC of 0.92 for retinopathy prediction
* Risk Stratification: Through cluster analysis, the research identified distinct patient risk groups, with high-risk clusters showing a 70% probability of cardiovascular complications within 5 years (compared to 20% in low-risk clusters).
* Early Detection Capabilities: The Decision Tree model demonstrated 88% sensitivity in identifying early-stage diabetic nephropathy, enabling timely intervention.
* Feature Importance Analysis: The study identified HbA1c levels, BMI, and diabetes duration as the most significant predictors for diabetic complications, providing valuable insights for personalized risk assessment.

**Comparison with Related Work:** The paper builds upon previous research in the field:

* Wang et al. (2018) explored ensemble methods for diabetic retinopathy prediction
* Li et al. (2020) used RNNs for cardiovascular event prediction in diabetic patients
* Smith et al. (2019) utilized SVMs for nephropathy risk stratification

This study advances the field by:

* Using a larger dataset (10,000 patients)
* Comparing multiple algorithms against the same dataset
* Providing comprehensive performance metrics across various complications
* Emphasizing clinical applicability through risk stratification

**Merits of the Work:**

* Comprehensive Methodology: The paper employs a diverse set of machine learning algorithms including logistic regression, random forest, SVMs, gradient boosting, and RNNs.
* Robust Evaluation Framework: The study uses multiple performance metrics (accuracy, precision, recall, F1-score, AUC) and cross-validation techniques to ensure reliable results.
* Clinical Relevance: The research directly addresses practical healthcare concerns by enabling early diagnosis and personalized treatment planning.
* Feature Engineering: The methodology includes advanced feature selection and engineering techniques to enhance predictive performance.

**Limitations and Gaps:**

* Model Interpretability: While the paper mentions the importance of model interpretability, it does not deeply explore techniques for making complex models like Random Forest and Gradient Boosting more interpretable to clinicians.
* Limited External Validation: The paper does not mention external validation on independent datasets, which would strengthen the generalizability of the findings.
* Absent Implementation Details: The methodology section mentions data preprocessing and feature selection but lacks specific details about implementation choices.
* Data Bias Considerations: The paper does not thoroughly address potential biases in the dataset or how these might impact model performance across different demographic groups.

**Relevance to our Project:** This paper aligns well with our healthcare data platform project in several ways:

* The machine learning models demonstrated for diabetic complications could be integrated into our platform's predictive analytics component, particularly for chronic condition detection.
* The paper's feature importance analysis provides insights into what patient data points are most critical for risk assessment, which should inform our data collection strategy.
* The risk stratification approach could be adapted for our dashboards to help healthcare providers quickly identify high-risk patients.
* The methodology sections on data preprocessing and model evaluation provide a framework that we could adopt for implementing ML components in our platform.

**For our project, we would like to consider:**

* Adapting the Random Forest and Gradient Boosting approaches that showed the highest performance
* Implementing a similar risk stratification system using clustering techniques
* Using the identified key features (HbA1c, BMI, diabetes duration) as core components of our patient profiles
* Incorporating model explainability techniques to help doctors understand and trust the predictions.

This research provides valuable evidence for the effectiveness of machine learning in healthcare risk assessment, supporting the core premise of our project's predictive analytics component.

2) (13)

**Summary:** This paper presents research identifying and ranking the top 15 design attributes for effective healthcare dashboards. Through a survey of 218 individuals across multiple US states, the researchers established design priorities that aim to improve how health information is presented to the public, ultimately enabling better-informed healthcare decisions and improved health outcomes.

**Main Contributions:** The research provides a comprehensive, evidence-based ranking of design attributes for healthcare dashboards:

1. Easy navigation (96% agreement)
2. Incorporated historical data (95%)
3. Simplicity of design (94%)
4. High usability (94%)
5. Use of clear descriptions (93%)
6. Consistency of data (93%)
7. Use of diverse chart types (91%)
8. Compliance with Americans with Disabilities Act (91%)
9. Incorporated user feedback (91%)
10. Mobile compatibility (89%)
11. Comparison data with other entities (88%)
12. Storytelling (88%)
13. Predictive analytics with artificial intelligence (87%)
14. Adjustable thresholds (85%)
15. Charts with tabulated data (83%)

The study notably includes five new attributes not previously explored in their research: storytelling, predictive analytics with AI, mobile compatibility, incorporated historical data, and consistency of data.

**Comparison with Other Work:** The paper builds upon prior research while making distinct contributions:

* Expands on the authors' previous study on COVID-19 dashboards (which surveyed 118 individuals for 10 key elements)
* Complements Ansari et al.'s work on usability problems in public health dashboards
* Extends Karami et al.'s 7 key concepts for effective dashboards to a more comprehensive set of 15 best practices
* Incorporates Murphy et al.'s recommendation that human factors and informatics principles should guide dashboard design
* Builds on Martins et al.'s best practices for business management dashboards by adapting them to healthcare contexts

**Merits of the Work:**

* Comprehensive scope: The researchers examined over 250 public-facing healthcare dashboards before conducting their survey.
* User-centered approach: The study prioritizes the needs and preferences of healthcare dashboard users.
* Focus on accessibility: The emphasis on ADA compliance and mobile compatibility demonstrates commitment to inclusive design.
* Forward-looking inclusion of AI: Recognizing the growing importance of predictive analytics in healthcare data visualization.
* Practical relevance: The findings provide actionable guidelines for dashboard designers to improve health information communication.
* Quantitative validation: Clear percentage-based rankings provide empirical support for design priorities.

**Limitations of the Work:**

* Geographic limitations: Over 70% of participants came from just three states (Maryland, West Virginia, and Virginia), limiting nationwide generalizability.
* Sample size constraints: The authors acknowledge that a larger sample (e.g., 1000+ participants with 5-10 per state) would strengthen the findings.
* Self-reporting limitations: The study relies on self-reported preferences rather than measuring actual decision-making outcomes from different dashboard designs.
* Lack of behavioral metrics: No data on whether improved dashboard design translates to better healthcare decisions in practice.
* Limited demographic diversity: While demographic information was collected, there's minimal analysis of how design preferences might vary across different demographic groups.

**Relevance to our Project:** This paper offers valuable insights for our integrated healthcare data platform project:

* Dashboard design principles: The ranked attributes provide a blueprint for designing effective visualizations of patient healthcare data.
* AI integration guidance: The findings on predictive analytics with AI align with our project's goal to implement machine learning for health risk assessment.
* User experience focus: The emphasis on navigation, usability, and simplicity should inform our platform's interface design.
* Data presentation strategies: Insights on historical data, comparison data, and diverse chart types can guide how we present comprehensive patient records.
* Accessibility considerations: The paper's attention to ADA compliance reinforces the importance of building an inclusive platform.
* Mobile integration: The recognition of mobile compatibility as a key attribute supports our goal of creating accessible healthcare insights.

**For our project specifically, we would like to prioritize the following from the paper:**

* Intuitive navigation between different data types (profiles, visits, medications)
* Clear data visualization with appropriate chart diversity
* Consistency in how patient data is presented across the platform
* Mobile-friendly design for healthcare provider access
* Implementing AI predictive analytics in an understandable, transparent way
* Ensuring the platform meets accessibility standards

3) (14)

**Summary:** Using raw electronic health record (EHR) data from two university institutions in the United States, the study investigates the use of deep learning for clinical outcome prediction. The authors trained models to predict outcomes like in-hospital mortality (AUROC 0.93–0.94), 30-day unplanned readmissions (AUROC 0.75–0.76), prolonged length of stay (AUROC 0.85–0.86), and discharge diagnoses (frequency-weighted AUROC 0.90) by presenting patient data in the FHIR (Fast Healthcare Interoperability Resources) format. By using unstructured data (such as clinical notes) and avoiding the need for human feature engineering, the models outperformed conventional clinical scoring systems and showed scalability across healthcare institutions.

**Main Contributions**

* Comprehensive Data Representation:
  + Utilizes the FHIR standard to encode the complete raw EHR data as a sequence of tokens.
  + Processes both structured data and free-text clinical notes, thus capturing the full complexity of patient records.
* Deep Learning Architectures:
  + Implements multiple deep learning models (e.g., LSTM-based recurrent neural networks, attention-based TANNs, and boosted time-based decision stumps).
  + Trains these models on multiple prediction tasks and at several time points (e.g., before admission, at admission, 24 hours after admission, and at discharge).
* Multiple Prediction Tasks:
  + In-hospital mortality: Achieved high AUROC scores (0.93–0.95), outperforming traditional scores (e.g., aEWS).
  + 30-day unplanned readmissions: Achieved AUROCs around 0.76–0.77, again better than traditional predictive models.
  + Prolonged length of stay: Demonstrated AUROC improvements (0.85–0.86 vs. 0.74–0.77 with baseline models).
  + Discharge diagnoses: Predicted a patient’s full set of ICD-9 discharge diagnoses with a micro-F1 score of approximately 0.40, outperforming earlier studies on smaller datasets.
* Early and Accurate Predictions:
  + The deep learning approach not only improves accuracy but also provides predictions earlier in the hospitalization process compared to conventional models.
* Interpretability and Attribution:
  + Introduces attribution mechanisms that highlight which data tokens influenced a particular prediction.
  + This is a crucial step toward addressing the “black box” criticism often directed at deep learning models in clinical settings.

**Comparison with Other Work:**

* Traditional Predictive Models:
  + Feature Engineering: Earlier methods depend on manually curated, often limited sets of predictor variables (median of 27 variables), which can miss the richness of the EHR.
  + Logistic Regression: Many traditional models (e.g., aEWS for mortality, modified HOSPITAL for readmission) show lower performance compared to the deep learning approach presented.
* Prior Deep Learning Approaches:
  + Previous studies have applied deep learning (e.g., autoencoders or simple recurrent networks) on datasets like MIMIC-III, typically focusing on specific patient subsets (e.g., ICU patients) or a narrower range of predictors.
  + This work distinguishes itself by processing billions of data points from a general hospital population and by combining multiple deep-learning architectures into an ensemble.
* Data Integration:
  + Unlike studies that require extensive data harmonization across sites, this paper shows that raw EHR data from two different hospitals (with minimal harmonization) can be effectively utilized in a scalable deep-learning framework.

**Merits of the Work**

* Scalability: The method can process and learn from extremely large volumes of EHR data without the need for manual feature extraction.
* Enhanced Predictive Performance: Consistently higher AUROC scores and improved detection metrics (e.g., lower false alert rates) across multiple prediction tasks.
* Early Intervention Potential: By achieving similar accuracy levels earlier in the patient’s course, the model holds promise for earlier clinical interventions.
* Inclusion of Unstructured Data: Incorporating free-text notes significantly broadens the range of available information, potentially leading to richer predictions.
* Model Interpretability: The attribution visualization helps clinicians understand which aspects of the EHR influenced a prediction, which is important for clinical trust and decision support.

**Limitations and Areas for Improvement**

* Retrospective Design: The study is retrospective; prospective validation is necessary to confirm clinical utility in real-world settings.
* Computational Complexity: The deep learning models are computationally intensive and currently require specialized expertise, which might limit their immediate deployment in some clinical settings.
* Data Harmonization and Transferability: While the approach works across two hospitals, the lack of standardized harmonization may challenge its application to new sites with different data characteristics.
* Granularity of Predictions: The study does not fully explore the incremental benefit of each data type (e.g., comparing structured data versus free text), leaving some questions about optimal model design open.
* Interpretability Challenges: Although attribution methods are employed, the overall “black box” nature of deep neural networks can still be a barrier to clinical adoption.

**Relevance to our Project:** Our project aims to build an integrated platform for managing and analyzing patient healthcare data, with features such as comprehensive dashboards, predictive analytics for health risk assessment, and secure data storage. This paper’s approach is highly relevant in several ways:

* Data Integration: The FHIR-based representation aligns with our goal to organize comprehensive patient records, ensuring that all relevant data, structured or unstructured can be incorporated.
* Predictive Analytics: The deep learning models described could inform the development of machine learning components in our platform, offering early and accurate predictions for critical outcomes like mortality, readmissions, and length of stay.
* Actionable Insights: The interpretability methods used in the study can help you design user-friendly visualizations that clearly communicate risk factors and predictive reasoning to both clinicians and patients.
* Scalability and Automation: The automated feature learning demonstrated in the paper shows promise for scaling analytics without manual data preprocessing, a key aspect of our integrated platform.

Overall, the paper provides a compelling demonstration of how deep learning can be leveraged to unlock the full potential of EHR data, both improving predictive performance and paving the way for more interpretable clinical decision support systems. This aligns closely with the vision of our project, offering valuable insights into both the technical and clinical challenges of building an advanced health data analytics platform.

4) (15)

**Summary:** Liu et al. (2024) conducted a systematic review and meta-analysis comparing machine learning (ML) models with conventional statistical approaches for predicting 5- to 10-year cardiovascular disease (CVD) risk using electronic health records (EHRs). Analyzing 20 studies from 2010 to 2024, including 32 ML models (e.g., random forest with a pooled AUC of 0.865 and deep learning with an AUC of 0.847) and 26 conventional models (e.g., QRISK3 with an AUC of 0.765), the study found that ML approaches generally outperformed traditional methods. However, significant heterogeneity (I² > 99%) and methodological inconsistencies were noted, highlighting the need for standardization before clinical adoption. The review adhered to PRISMA guidelines and focused on primary prevention models using structured EHR data.

**Main Contributions:**

* Advancement in Risk Prediction Paradigms: The study provides the first comprehensive meta-analysis quantifying ML’s superiority over conventional CVD risk scores. By pooling AUC metrics, the authors demonstrate that ML models improve discrimination by 8–13% compared to QRISK3 and ASCVD. This enhancement stems from ML’s ability to capture nonlinear interactions and high-dimensional patterns in EHR data, which traditional linear models often miss.
* Identification of Heterogeneity Sources: Through subgroup analyses, the review uncovers critical variability in model performance linked to geographical disparities (e.g., UK vs. US datasets), EHR completeness, and outcome definitions. For instance, models trained on UK Biobank data exhibited better calibration due to standardized EHR structures, whereas US models showed higher discrimination but poorer generalizability.
* Framework for Model Evaluation: The authors propose a quality assessment rubric addressing common pitfalls in ML for health research, including overfitting risks, incomplete hyperparameter reporting, and lack of external validation. They emphasize that only 35% of reviewed studies performed temporal or geographical validation, limiting clinical applicability.

**Comparison with Existing Work:**

* Conventional Risk Scores: QRISK3 and ASCVD, grounded in Cox regression and pooled cohort equations, remain clinical mainstays due to interpretability and guideline endorsements. However, their reliance on linear assumptions and static variables (e.g., age, blood pressure) renders them less adaptable to evolving risk factors like lifestyle changes or comorbidities.
* Prior ML Studies in CVD: Earlier systematic reviews, such as those by Al’Aref et al. (2019) and Dinh et al. (2021), highlighted ML’s potential but lacked quantitative synthesis. Liu et al. advance the field by statistically aggregating performance metrics, revealing consistent but variable ML advantages. For example, while deep learning excelled in image-based CVD prediction, its EHR-based performance trailed ensemble methods; a nuance absent in prior literature.
* EHR-Specific Challenges: Unlike cohort studies (e.g., Framingham), EHR-derived datasets introduce noise from missing entries and coding inconsistencies. The review notes that ML models employing data imputation techniques (e.g., multiple imputation by chained equations) achieved 15% higher AUCs than models ignoring missingness, aligning with findings from Wong et al. (2023) on EHR data curation.

**Merits of the Study:**

* Quantitative Synthesis of Heterogeneous Evidence: By applying random-effects meta-analysis, the authors account for variability across healthcare systems and EHR platforms. The pooled AUCs provide clinicians with benchmark metrics for evaluating emerging ML tools against familiar standards like QRISK3.
* Clinical Relevance and Translation: The review bridges computational and clinical domains by discussing implementation barriers. For instance, it notes that ML models integrating unstructured EHR data (e.g., clinician notes) showed promise but required specialized NLP pipelines absent in most healthcare IT systems.
* Methodological Transparency: Detailed appendices document search strategies, inclusion criteria, and risk-of-bias assessments using PROBAST (Prediction Model Risk of Bias Assessment Tool). This transparency enables replication and informs future study designs.

**Failings and Limitations:**

* High Heterogeneity Undermining Conclusions: The extreme heterogeneity (I² > 99%) reflects disparate study designs, from single-center trials to multinational registries. This precludes definitive conclusions about optimal algorithms or feature sets, as contextual factors heavily influence performance.
* Publication Bias and Overoptimism: Funnel plot asymmetry suggests small studies with negative results remain unpublished. Additionally, many included studies used AUC-optimized thresholds rather than clinically actionable risk cut-offs, inflating perceived utility.
* Lack of Standardized Reporting: Only 40% of studies provided full model specifications or code repositories. This opacity hinders independent validation and clinical adoption, echoing concerns raised by the MI-CLAIM checklist for ML in healthcare.

**Relevance to our Project:**

* Predictive Analytics Foundation: The review validates the project’s emphasis on ML driven risk assessment. For instance, adopting ensemble methods could enhance predictive accuracy for chronic conditions beyond CVD, such as diabetes or renal disease, by leveraging structured EHR variables.
* Data Infrastructure Considerations: Findings underscore the importance of EHR data quality and completeness. The project’s secure storage platform must incorporate robust imputation and normalization pipelines to mitigate biases identified in heterogeneous datasets.
* Clinical Integration Challenges: Compatibility with existing EHR systems is critical. The paper’s discussion on interoperability barriers aligns with our project’s aim to seamlessly integrate analytics tools without disrupting clinician workflows.
* Patient Engagement Opportunities: Superior risk stratification via ML enables personalized educational content delivery. For example, high-risk patients flagged by models could receive targeted lifestyle modification guides, enhancing preventive care.

**Future Directions and Recommendations**

* Model Standardization and Reporting: Adopt frameworks like TRIPOD-ML (Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis in Machine Learning) to ensure reproducibility. The platform should log hyperparameters, training epochs, and validation protocols for auditability.
* Multimodal Data Integration: Incorporate unstructured data (imaging, genomics) while addressing computational demands. Federated learning approaches could enable model training across institutions without raw data sharing, aligning with our project’s security goals.
* Real-World Validation: Implement prospective trials comparing platform-generated insights against standard care. Metrics should extend beyond AUC to clinical outcomes like prevented adverse events and cost savings.

In conclusion, Liu et al.’s systematic review provides robust evidence supporting ML’s role in CVD risk prediction while cautioning against premature clinical deployment. The proposed healthcare platform can address these limitations through rigorous validation, transparent reporting, and seamless EHR integration, ultimately advancing personalized preventive care.

5) **(16)**

**Summary**

This paper presents a smart healthcare monitoring system aimed at enhancing heart disease prediction accuracy by integrating wearable sensors and electronic medical records (EMRs). The proposed system leverages ensemble deep learning combined with feature fusion techniques, ensuring a comprehensive approach to data analysis. The feature selection process employs information gain and conditional probability to eliminate irrelevant and redundant data, ultimately enhancing computational efficiency and predictive performance. The ensemble deep learning model is then trained using the optimized dataset, leading to an impressive prediction accuracy of 98.5%. Additionally, an ontology-based recommendation system is incorporated, providing personalized health recommendations based on individual patient data.

**Main Contributions:**

* Data Fusion: Merges real-time sensor data with EMRs to create a comprehensive dataset.
* Feature Selection: Employs information gain and conditional probability to filter out redundant data.
* Deep Learning Ensemble: Utilizes multiple deep learning models combined with LogitBoost to enhance accuracy.
* Ontology-Based Recommendations: Generates personalized health recommendations using Semantic Web Rule Language (SWRL).

**Comparison with Other Works:**

Compared to QRISK3, which is primarily designed for long-term risk assessment using structured medical data, this system enables real-time monitoring by integrating sensor data. However, unlike MSSO-ANFIS, which optimizes feature selection through a metaheuristic approach, this model requires extensive preprocessing to manage large datasets. While CNN-based models process unstructured data, this system remains focused on structured EMRs and sensor readings, ensuring more reliable but less flexible predictions.

**Merits of the Work:**

* High accuracy (98.5%), outperforming traditional machine learning models.
* Feature selection minimizes computational overhead and improves efficiency.
* Personalized recommendations enhance patient care beyond simple diagnostics.

**Limitations and Areas of Improvement:**

* High computational complexity, requiring substantial processing power.
* Limited flexibility in handling unstructured data, unlike CNN-based models.
* Scalability concerns when integrating large datasets from multiple sources.

**Relevance to the Project:**This study is highly relevant as it aligns with the goal of integrating wearable sensor data with machine learning models for real-time heart disease prediction. The ensemble deep learning model can be adapted to improve accuracy in our system.

**Future Directions and Recommendations:**

* Explore hybrid models combining deep learning with neuro-fuzzy techniques for better adaptability.
* Enhance real-time processing by optimizing feature extraction and selection.
* Expand the dataset to include more diverse demographics for improved generalizability.

6) **(17)**

**Summary:**

This study presents an IoMT-based heart disease monitoring system that integrates Modified Salp Swarm Optimization (MSSO) with Adaptive Neuro-Fuzzy Inference System (ANFIS) to improve prediction accuracy. The model achieves 99.45% accuracy, optimizing ANFIS learning using Levy-based Crow Search Algorithm (LCSA).

**Main Contributions:**

* Metaheuristic optimization (MSSO) for feature selection.
* Enhanced ANFIS model to avoid local minima.
* Real-time IoMT monitoring capabilities.

**Comparison with Existing Work:**

* Outperforms ensemble deep learning in accuracy but has higher computational cost.
* Unlike QRISK3, which is optimized for long-term risk prediction, this system focuses on real-time diagnosis.
* Does not handle unstructured data like CNN-based models but excels in structured medical data processing.

**Merits:**

* Exceptional accuracy (99.45%).
* Effective feature selection improves learning efficiency.
* Real-time monitoring capabilities.

**Limitations:**

* High computational demands.
* Complex parameter tuning.
* Dependence on IoMT infrastructure.

**Relevance to the Project:**

This study provides a strong foundation for integrating **IoMT technologies** with heart disease prediction.

**Future Directions:**

* Optimize computational efficiency.
* Improve scalability through cloud-based deployment.
* Extend functionality for broader cardiovascular health monitoring.

7) **(18)**

**Smmary:**

QRISK3 is an advanced statistical risk prediction algorithm that estimates 10-year cardiovascular disease risk. The model incorporates additional risk factors such as systolic blood pressure variability, chronic kidney disease, and mental health conditions, improving upon previous versions like QRISK2.

**Main Contributions:**

* Expanded risk factors for better long-term risk assessment.
* Validated on a massive dataset of 10 million patients.
* Clinically adopted in healthcare settings.

**Comparison with Existing Work:**

* Unlike real-time prediction models, QRISK3 is designed for long-term risk evaluation.
* More clinically interpretable than deep learning-based models.
* Lacks real-time adaptability seen in IoMT-based models.

**Merits:**

* Highly validated and clinically adopted.
* Easily interpretable statistical model.

**Limitations:**

* Not suitable for real-time predictions.
* Lacks adaptability to evolving patient data trends.
* Relevance to the Project: QRISK3 can be integrated into our predictive models to enhance long-term cardiovascular risk assessment.

**Future Directions:**

* Incorporate real-time monitoring alongside long-term risk assessment.
* Adapt QRISK3 for mobile-based risk prediction.
* Enhance usability through user-friendly applications.

8) **(19)**

**Summary:**

This paper presents a CNN-based multimodal disease prediction system using structured and unstructured data. The model integrates hospital records and patient narratives to improve predictive accuracy, achieving 94.8% accuracy.

**Main Contributions:**

* Combines structured and unstructured medical data.
* Utilizes CNNs for feature extraction.
* Employs a latent factor model to handle missing data.

**Comparison with Existing Work:**

* More flexible than QRISK3, which only handles structured data.
* Unlike ensemble deep learning, it integrates text-based patient narratives.
* More computationally expensive than MSSO-ANFIS but handles more diverse data sources.

**Merits:**

* Handles both structured and unstructured data.
* High predictive accuracy (94.8%).

**Limitations:**

* High computational cost.
* Limited generalizability due to regional data bias.

**Relevance to the Project:**

Provides valuable insights into multimodal machine learning integration for heart disease prediction.

**Future Directions:**

* Optimize computational efficiency.
* Expand datasets for global applicability.
* Improve real-time processing capabilities.

9)    
**Article Title:** Simulation of a machine learning-enabled learning health system for risk prediction using synthetic patient data

**Summary of the Study**

Chen and Chen (2022) propose a simulated ML-enabled LHS designed for risk prediction in healthcare. The study employs synthetic patient data generated by Synthea, a tool that mimics real-world patient data while avoiding privacy concerns. The authors develop an XGBoost-based risk prediction model for lung cancer, progressively improving its accuracy by incrementally adding more synthetic patient data. Their approach is then verified by applying the same methodology to stroke risk prediction, demonstrating the adaptability of their ML-enabled LHS. The study evaluates model performance using AUC metrics and highlights the importance of iterative model improvement through continuous learning cycles.

**Key Contributions**

The study introduces a data-centric approach to LHS, which emphasizes continuous data updates to refine predictive models. Unlike traditional algorithm-centric ML models that focus on tuning algorithms, this study underscores the importance of improving data quality and quantity. Another major contribution is the public availability of both the ML code and synthetic patient data, facilitating further research. Furthermore, the study successfully showcases how synthetic data can be used to simulate real-world ML applications, overcoming privacy constraints associated with electronic health records (EHRs).

**Comparison with Existing Work**

While previous studies have explored ML applications in healthcare, most rely on real patient data, making replication and further advancements challenging due to privacy restrictions. For example, Wang et al. (2019) developed an ML-based lung cancer risk prediction model using real EHR data, achieving an AUC of 0.88. In contrast, Chen and Chen's (2022) synthetic data approach achieved an AUC of 0.96, highlighting its potential for model training without privacy risks. Other studies, such as Yeh et al. (2021), focused on deep learning models for lung cancer prediction, yet lacked the continuous learning aspect that this study integrates into its LHS framework.

Additionally, unlike models that require extensive data imputation for handling missing values, the synthetic data approach eliminates this issue by providing complete patient records. However, some existing works leverage hybrid models combining deep learning with traditional ML techniques, which were not explored in this study.

**Relevance to the Project**

This study directly aligns with our project, developing a Healthcare Monitoring System with a Comprehensive Dashboard, as it explores the application of machine learning in health risk prediction. The integration of synthetic data generation techniques, as demonstrated by Chen and Chen (2022), can be beneficial for our project when designing predictive analytics models. The study also highlights the importance of continuous learning and data updates, which is a key feature of our healthcare system. Additionally, the research provides insights into how predictive models, such as XGBoost, can be incorporated into our platform for early detection of diseases. By leveraging similar methodologies, our project aims to provide a scalable, privacy-preserving, and data-driven healthcare monitoring system that enables real-time risk assessment and patient-centric decision support through an interactive dashboard.

**Merits and Strengths**

* **Use of Synthetic Data -** The study demonstrates how synthetic patient data can effectively train ML models while maintaining privacy.
* **Data-Centric Approach -** The iterative methodology ensures continuous improvement in model accuracy with incremental data updates.
* **Open Access -** The availability of ML code and synthetic datasets allows other researchers to build upon the findings.

**Limitations and Challenges**

* **Synthetic vs. Real Data** - Although synthetic data is useful, it does not fully replicate the complexity of real-world patient data.
* **Generalizability -** The findings may not directly translate to actual clinical settings without additional real-world validation.
* **Algorithm Scope -** The study primarily focuses on XGBoost and does not extensively explore deep learning techniques.

10)

**Article Title:** Intelligent health risk prediction systems using machine learning: A review

**Summary of the Study**

Shinde and Rajeswari (2018) provide a detailed review of ML applications in health risk prediction. Their study categorizes ML methods into supervised, unsupervised, semi-supervised, reinforcement, and deep learning techniques. The authors explore various ML models, such as classification, clustering, regression, and optimization, applied to EHRs for disease prediction. The study also examines binary and multi-class classification techniques used in health informatics, emphasizing the role of ML in developing intelligent decision-support systems. Additionally, the study highlights key assumptions made in different ML models and the challenges posed by noisy and incomplete medical datasets.

**Key Contributions**

* **Categorization of ML Methods -** The paper systematically classifies ML techniques based on their learning paradigms and problem-solving approaches.
* **Survey of Health Risk Prediction Models -** A broad analysis of existing ML-based disease prediction systems is provided.
* **Challenges in ML Applications -** The study highlights difficulties in handling incomplete and noisy biomedical datasets.
* **Future Research Directions -** The authors suggest improvements in data quality, feature selection, and ML model optimization.

**Comparison with Existing Work**

Unlike studies that focus on a single disease or specific ML approach, Shinde and Rajeswari (2018) take a broader view, categorizing different ML techniques used in health risk prediction. Wu et al. (2017), for example, implemented ML models for breast cancer risk assessment, demonstrating high accuracy but limited generalizability to other conditions. Similarly, Yeh et al. (2021) explored deep learning models for lung cancer prediction, focusing on neural networks rather than traditional ML techniques. This review distinguishes itself by providing an overarching comparison of various ML methods, making it a valuable resource for understanding how different models can be applied to multiple health conditions.

**Relevance to the Project**

Our project integrates predictive analytics to assess patient risks using historical data, and the categorization of ML techniques in this study helps in identifying the most suitable approaches for implementation. Additionally, the study’s discussion on handling noisy and incomplete data directly applies to our goal of improving data processing in healthcare systems. By incorporating findings from this review, we can enhance our model selection process, optimize risk assessment algorithms, and ensure our system provides reliable and scalable healthcare solutions.

**Merits and Strengths**

* **Comprehensive ML Categorization -** The study effectively organizes ML techniques, making it easier for new researchers to understand the field.
* **Broad Application Scope -** Covers multiple diseases and ML approaches rather than focusing on a single health condition.
* **Identification of Challenges -** Discusses real-world challenges in applying ML to healthcare, such as data quality and computational constraints.

**Limitations and Challenges**

* **Lack of Experimental Validation -** The study reviews existing methods but does not implement or test any specific ML model.
* **Generalization Issues -** Covers a wide range of techniques without providing in-depth analysis of their individual effectiveness.
* **Limited Focus on Deep Learning -** While deep learning is mentioned, the study does not explore its potential in detail.
* **Challenges in Data Processing -** Highlights data-related issues but does not propose concrete solutions for overcoming them.

11)

**Article Title:** Health risk assessment using machine learning: Systematic review

**Summary of the Study**

Abhadiomhen et al. (2024) conduct a systematic review of ML applications in HRA. Using a structured three-phase approach, they analyze 26 peer-reviewed studies from five databases. The study highlights that 42% of these studies focus on general health risks, while others target specific conditions. Secondary data sources dominate, with random forest emerging as the most frequently used algorithm. Additionally, the study identifies a gap in diverse sample representation and emphasizes the need for improving model interpretability to enhance trustworthiness in healthcare applications.

**Key Contributions**

* **Comprehensive Review -** It systematically categorizes ML applications in HRA, differentiating between general and condition-specific assessments.
* **Analysis of Data Sources -** Highlights the reliance on secondary datasets and the underrepresentation of diverse populations.
* **Popular ML Algorithms -** Identifies random forest as the most utilized algorithm, followed by ensemble methods and deep learning techniques.

**Comparison with Existing Work**

Compared to previous studies, Abhadiomhen et al. (2024) adopt a broader perspective on ML applications in HRA compared to previous studies. While some studies, such as Mishra et al. (2024), focus primarily on pancreatic cancer prediction using EHRs, this review evaluates multiple conditions, making its findings more generalizable. Similarly, Singh et al. (2024) investigate AI-driven risk assessments for cardiovascular diseases, placing emphasis on individualized predictions. However, unlike these disease-specific studies, Abhadiomhen et al. (2024) provide a more inclusive analysis, allowing for a comparative understanding of ML methodologies across different health risks. By synthesizing diverse research, this review serves as a valuable reference for identifying cross-applicable ML strategies in healthcare.

**Relevance to the Project**

Since our project involves implementing predictive analytics for health risk assessment, understanding the effectiveness of different ML models is crucial. The review’s identification of frequently used algorithms, such as random forest and ensemble methods, provides insight into potential model selection for our system. Additionally, the study’s emphasis on improving model interpretability aligns with our goal of making predictions accessible to both healthcare professionals and patients. By integrating these insights, our project aims to develop a scalable, data-driven, and user-friendly monitoring system that facilitates real-time risk assessment and personalized health recommendations.

**Merits and Strengths**

* **Comprehensive Scope -** Covers a wide range of ML techniques and their applications in different health risk assessments.
* **Identification of Research Gaps -** Highlights the need for diverse datasets and improved interpretability.
* **Systematic Methodology -** Follows a structured approach adhering to PRISMA guidelines, ensuring the reliability of findings.
* **Emphasis on Model Interpretability -** Raises awareness of the need for transparent ML models in healthcare.

**Limitations and Challenges**

* **Lack of Experimental Validation -** The study reviews existing literature but does not implement ML models for performance comparison.
* **Over-Reliance on Secondary Data -** Many included studies use publicly available datasets, limiting real-world applicability.
* **Generalization Issues -** The study acknowledges that existing ML models lack validation on diverse populations.

12)

**Article Title:** Integrated convolutional and recurrent neural networks for health risk prediction using patient journey data with many missing values

**Summary of the Study**

Liu et al. (2022) propose a novel end-to-end deep learning model that integrates CNNs and RNNs for health risk prediction. Unlike conventional methods that rely on imputing missing EHR data, their model processes missing values without generating synthetic data, thereby preserving clinical accuracy. The CNN component captures short-term temporal patterns within patient records, while the Gated Recurrent Unit (GRU) models long-term dependencies. Experimental results on real-world datasets show superior performance compared to state-of-the-art imputation-based models.

**Key Contributions**

* **Integration of CNN and RNN -** Combines CNNs for short-term dependencies and RNNs for long-term relationships in patient data.
* **Handling Missing Data Without Imputation -** Avoids the bias introduced by imputed values, ensuring data integrity.
* **End-to-End Learning Model -** Provides a robust deep learning architecture that directly processes raw EHR data.
* **Comparison with Existing Models -** Demonstrates higher predictive accuracy than traditional imputation-based methods.

**Comparison with Existing Work**

Liu et al. (2022) present an innovative approach to handling missing data, setting them apart from earlier studies. For instance, Che et al. (2018) relied on data imputation techniques for managing missing values in recurrent neural network models. While effective, their approach introduced the risk of artificial biases affecting model accuracy. Similarly, Tan et al. (2020) implemented attention-based GRUs for health risk prediction but did not incorporate CNNs to capture localized temporal patterns. In contrast, Liu et al. (2022) designed an architecture that preserves original patient data while leveraging deep learning techniques for enhanced predictive power. Their framework improves both short-term and long-term patient outcome prediction by eliminating the reliance on imputed values.

**Relevance to the Project**

One of the primary challenges in predictive analytics is handling missing or incomplete patient data. Liu et al. (2022) address this issue by integrating CNNs and RNNs, a concept that could be adapted for our predictive analytics module. Additionally, their emphasis on real-time processing supports our objective of developing a system that provides timely health risk assessments. By incorporating elements of their model, we can enhance our project’s scalability, accuracy, and clinical applicability, ensuring that patient data is analyzed efficiently without requiring artificial imputation methods.

**Merits and Strengths**

* **Eliminates Data Imputation Bias -** Maintains clinical integrity by avoiding artificial data generation.
* **Enhanced Temporal Feature Extraction -** CNNs capture short-term patterns, while RNNs handle long-term dependencies.
* **Improved Prediction Accuracy -** Outperforms state-of-the-art models on multiple ICU datasets.

**Limitations and Challenges**

* **Computational Complexity -** Deep learning models require significant processing power and memory.
* **Limited Interpretability -** CNN-RNN architectures lack transparency in decision-making processes.
* **Dependency on High-Quality Data -** Although it avoids imputation, the model still relies on structured EHR inputs.
* **Generalization Concerns -** The approach may not generalize well to healthcare settings with highly heterogeneous data.

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**Literature Review on Healthcare Monitoring Dashboards**

**Introducton**

Healthcare monitoring dashboards serve as essential tools in the healthcare industry by offering real-time data visualization, decision support, and performance monitoring capabilities. This review evaluates recent studies on the requirements, challenges, and impacts of dashboards while identifying techniques for effective requirements elicitation in the development of these systems.

### **Requirements and Challenges of Hospital Dashboards**

**Rabiei & Almasi (2022)** conducted a systematic literature review to identify the functional and non-functional requirements of hospital dashboards. These include features like reporting, reminders, customization, tracking, alert creation, and performance assessment. The study also highlighted key challenges, such as data source integration, content design, and system interoperability.

* **Main Contributions**: This work provides a comprehensive analysis of requirements and challenges, offering developers insights into dashboard implementation complexities.
* **Comparison**: Unlike broader reviews, Rabiei and Almasi delve deeply into both functional and non-functional aspects, making this a valuable resource for understanding dashboard intricacies.
* **Merits**: The paper presents a thorough analysis supported by extensive literature.
* **Failings**: The absence of real-world case studies limits its practical applicability (Rabiei & Almasi, 2022).

### **Dashboard Technologies for Lipid Management**

**Samadbeik et al. (2024)** explored dashboard technologies for lipid management, focusing on their contributions to the quadruple aim of healthcare: improving population health, clinical outcomes, provider work-life, and patient experience.

* **Main Contributions**: This scoping review identifies specific benefits of dashboards in lipid management and evaluates their impact on healthcare outcomes.
* **Comparison**: While Rabiei and Almasi provide a broader analysis of dashboards, Samadbeik et al. focus on a specific application, offering detailed insights into lipid management.
* **Merits**: The study emphasizes targeted applications and provides evidence of their benefits.
* **Failings**: The findings are less generalizable to other areas of healthcare (Samadbeik et al., 2024).

### **Dashboards for Improving Patient Care**

**Dowding et al. (2015)** reviewed the use of dashboards to improve patient care, focusing on quality indicators and decision support systems. The review synthesized evidence on dashboard effectiveness in enhancing patient outcomes and care delivery processes.

* **Main Contributions**: The study provides a broad overview of dashboard applications across various healthcare settings, making it a useful reference for general implementation.
* **Comparison**: Unlike Samadbeik et al. (2024), this paper offers a less focused but more comprehensive analysis of dashboard applications.
* **Merits**: It provides practical recommendations and a detailed examination of quality indicators.
* **Failings**: The absence of recent data may limit its relevance to modern dashboard technologies (Dowding et al., 2015).

### **Requirements Elicitation Techniques**

**Sruthy (2025)** outlined top requirements elicitation techniques such as stakeholder analysis, brainstorming, and document analysis. Similarly, **Project Practical Editorial Team (2025)** provided a comprehensive checklist of elicitation methods, including interviews, surveys, and focus groups.

* **Main Contributions**: These articles provide practical insights and tools for gathering accurate requirements, essential for healthcare dashboard development.
* **Comparison**: While academic reviews like Rabiei & Almasi (2022) focus on theoretical analysis, these resources are more practitioner-oriented.
* **Merits**: The step-by-step descriptions make these resources accessible and actionable.
* **Failings**: Both works lack empirical validation and academic rigor (Sruthy, 2025; Project Practical Editorial Team, 2025).

**Morgan (2025)** emphasized crafting effective problem statements with clarity and focus, offering practical guidelines. Although beneficial for project managers, it lacks detailed academic analysis, making it more suitable for industry use.

### **Requirements Elicitation Plan**

**Techniques**:

1. **Interviews**: Engage healthcare professionals to understand system needs and challenges.
2. **Surveys**: Collect quantitative data from patients and providers to identify patterns and preferences.
3. **Document Analysis**: Review patient records, clinical guidelines, and previous dashboard implementations to uncover relevant requirements.
4. **Workshops**: Facilitate brainstorming sessions with stakeholders to collaboratively identify potential solutions.

**Research**:

* Conduct a literature review to identify best practices and common challenges in dashboard implementation.
* Analyze case studies of successful dashboard implementations to extract actionable insights.

**Literature Review**:

* Review academic papers and industry reports on healthcare monitoring dashboards to understand their effectiveness and limitations.

### **Updated Problem Statement**

The existing healthcare monitoring dashboard is inadequate in its ability to:

1. Monitor patient lab results effectively.
2. Predict the impact of medications accurately.
3. Provide personalized health recommendations based on EHR data.

The enhanced dashboard system will address these gaps, leading to improved patient outcomes, reduced healthcare costs, and higher quality of care.

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Timeline Update

Project Timeline:

1. Week 1: Conduct interviews and surveys with stakeholders.

2. Week 2: Analyze survey results and update the problem statement.

3. Week 3: Review literature and document analysis.

4. Week 4: Organize workshops and brainstorm potential solutions.

5. Week 5: Develop and test the enhanced dashboard.

6. Week 11: Finalize the dashboard and prepare the project report.