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AN ARTIFICIAL INTELLIGENCE-DRIVEN COMPUTATIONAL FRAMEWORK FOR PERSONALIZED DRUG DELIVERY AND DOSAGE OPTIMIZATION IN CHRONIC DISEASE MANAGEMENT

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Abstract - Chronic diseases such as diabetes, cardiovascular disorders, hypertension, and chronic kidney disease require long-term pharmacological treatment and continuous dosage management. Variations in patient characteristics, disease progression, physiological responses, and medication adherence often influence therapeutic outcomes. Conventional dosage determination approaches generally rely on standardized treatment guidelines that may not fully account for individual patient variability. Artificial intelligence techniques provide opportunities to analyze patient-specific clinical information and support personalized therapeutic decision-making. This paper presents an Artificial Intelligence-Driven Computational Framework (AICF) for personalized drug delivery and dosage optimization in chronic disease management. The proposed framework integrates patient clinical records, physiological measurements, treatment history, and medication response data within a machine learning-based decision support system. Feature engineering, predictive modeling, and explainability analysis are employed to estimate personalized dosage recommendations and optimize drug administration strategies. A Random Forest-based prediction model is utilized to identify appropriate dosage levels, while Shapley Additive Explanations (SHAP) are incorporated to improve interpretability and identify influential clinical factors. Experimental evaluation is conducted using chronic disease management datasets containing patient demographics, laboratory measurements, medication records, and treatment outcomes. Performance is assessed using accuracy, precision, recall, and F1-score metrics. Results demonstrate that the proposed framework effectively supports dosage prediction while providing interpretable explanations regarding treatment recommendations. The findings indicate that artificial intelligence-assisted decision support systems may contribute to individualized drug delivery planning and support evidence-based chronic disease management.

Keywords— *Personalized Medicine, Drug Delivery Systems, Dosage Optimization, Artificial Intelligence, Clinical Decision Support, Explainable Artificial Intelligence.*

INTRODUCTION

Chronic diseases represent one of the most significant healthcare challenges worldwide and account for a substantial proportion of long-term morbidity, mortality, and healthcare expenditure. Conditions such as diabetes mellitus, hypertension, cardiovascular disease, chronic kidney disease, and chronic respiratory disorders often require continuous medical management and prolonged pharmacological treatment. Effective disease control depends not only on medication selection but also on appropriate dosage determination tailored to individual patient characteristics [1]. Variability in patient physiology, disease progression, lifestyle factors, and treatment response can significantly influence therapeutic outcomes, making personalized treatment strategies increasingly important in modern healthcare. Conventional drug dosing approaches are generally based on standardized clinical guidelines developed from population-level studies. Although these guidelines provide an important foundation for clinical practice, they may not adequately account for individual differences in age, body weight, metabolic function, disease severity, genetic factors, and medication response [2]. Consequently, patients receiving similar treatments may experience different therapeutic outcomes, adverse effects, or treatment failures. These limitations have contributed to growing interest in personalized medicine approaches that seek to optimize treatment decisions based on patient-specific information. Personalized drug delivery aims to improve therapeutic effectiveness by tailoring medication administration strategies according to individual patient characteristics and clinical conditions. In chronic disease management, personalized dosing can help maintain therapeutic drug concentrations, reduce adverse reactions, improve treatment adherence, and enhance overall patient outcomes [3]. However, determining optimal dosage levels remains a complex task because numerous clinical variables influence drug absorption, distribution, metabolism, and response.

The increasing availability of electronic health records, laboratory measurements, wearable health monitoring systems, and clinical databases has generated large volumes of patient-related information. These data sources provide opportunities for data-driven healthcare decision-making and predictive analytics. Artificial Intelligence (AI) techniques have demonstrated considerable potential for extracting meaningful patterns from healthcare data and supporting clinical decision-making processes [4]. Machine learning algorithms can analyze complex relationships among clinical variables and identify factors associated with treatment effectiveness, disease progression, and medication response. Several studies have investigated the application of machine learning techniques for disease risk prediction, treatment recommendation, medication management, and clinical outcome forecasting [5]. In the context of chronic disease management, predictive models can assist healthcare professionals in identifying suitable treatment strategies and estimating dosage requirements based on individual patient profiles. Such approaches have the potential to support evidence-based therapeutic decisions while reducing reliance on generalized treatment recommendations. Despite the increasing adoption of AI in healthcare, concerns regarding model transparency remain an important challenge. Many machine learning systems operate as black-box models that provide limited information regarding the reasoning behind their recommendations. In clinical environments, healthcare professionals require understandable explanations before incorporating algorithm-generated recommendations into patient care [6]. Explainable Artificial Intelligence (XAI) techniques provide mechanisms for interpreting model predictions and identifying influential clinical variables contributing to decision outcomes.

To address these challenges, this paper proposes an Artificial Intelligence-Driven Computational Framework for personalized drug delivery and dosage optimization in chronic disease management. The framework integrates patient demographic information, clinical measurements, medication history, and treatment response indicators within a machine learning-based decision support architecture. The overall architecture of the proposed artificial intelligence-driven dosage optimization framework is illustrated in Fig. 1.The primary contributions of this study are threefold. First, a comprehensive AI-based framework is developed for personalized dosage optimization. Second, machine learning techniques are employed to generate patient-specific dosage recommendations using clinical and treatment-related information. Third, explainability analysis is incorporated to improve transparency and support clinical interpretation of dosage recommendations.

I. RELATED WORK

Personalized medicine has emerged as an important paradigm in modern healthcare, emphasizing the adaptation of therapeutic interventions according to individual patient characteristics. In chronic disease management, personalized treatment strategies aim to improve therapeutic effectiveness while minimizing adverse drug reactions

and treatment-related complications. Advances in healthcare informatics, clinical analytics, and artificial intelligence have contributed significantly to the development of personalized treatment models capable of supporting individualized drug delivery and dosage optimization. Traditional approaches to dosage determination primarily rely on population-based clinical guidelines and physician expertise. These methods utilize standardized treatment protocols developed from clinical trials and epidemiological studies. Although such guidelines provide a strong foundation for clinical practice, they may not adequately account for patient-specific variability in physiological characteristics, disease severity, pharmacokinetics, and treatment response [1]. Consequently, researchers have increasingly explored computational methods capable of supporting individualized therapeutic decisions.

Clinical Decision Support Systems (CDSSs) have been widely investigated as tools for assisting healthcare professionals in treatment planning and medication management. Early decision support systems were predominantly rule-based and relied on predefined clinical knowledge and expert-designed protocols [2]. These systems provided recommendations based on explicit clinical rules but often lacked flexibility when handling complex patient data and evolving treatment conditions. As healthcare datasets expanded in size and complexity, data-driven approaches gradually gained attention as alternatives to traditional rule-based systems. Machine learning techniques have become increasingly important in healthcare analytics due to their ability to identify hidden relationships within large clinical datasets. Researchers have applied various machine learning algorithms, including Decision Trees, Support Vector Machines (SVMs), Random Forests, Artificial Neural Networks, and Gradient Boosting methods, to predict disease outcomes, treatment effectiveness, and medication requirements [3]. These techniques enable the analysis of multiple clinical variables simultaneously and can generate predictive models capable of supporting therapeutic decision-making.

Several studies have investigated machine learning applications for dosage prediction and medication optimization. In diabetes management, predictive models have been developed to estimate insulin requirements using blood glucose measurements, dietary information, and physiological characteristics [4]. Similar approaches have been employed in anticoagulant therapy, where machine learning algorithms have been used to predict individualized warfarin dosage requirements based on patient demographics, clinical indicators, and genetic information [5]. Researchers have also explored predictive analytics for hypertension management, chronic kidney disease treatment, and cardiovascular therapy optimization. The growing availability of electronic health records has further accelerated research in personalized treatment recommendation systems. Healthcare databases contain diverse information regarding patient demographics, laboratory measurements, medication histories, disease progression, and treatment outcomes. Machine learning models trained on such datasets can identify patterns associated with therapeutic effectiveness and assist clinicians in selecting appropriate treatment strategies [6]. Random Forest-based approaches have demonstrated particular effectiveness because of their robustness, ability to handle heterogeneous healthcare data, and resistance to overfitting. Despite advancements in predictive healthcare analytics, interpretability remains an important concern. Many machine learning models operate as black-box systems, making it difficult for healthcare professionals to understand the factors influencing recommendations. Clinical adoption of predictive systems often depends on the availability of transparent explanations that justify treatment suggestions and dosage recommendations [7].

Explainable Artificial Intelligence (XAI) techniques have emerged as a promising solution to this challenge. Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) provide mechanisms for quantifying feature contributions and interpreting model predictions [8], [9]. In healthcare applications, explainability techniques have been employed to identify influential clinical variables, improve transparency, and support evidence-based decision-making. These methods enable clinicians to understand why a particular recommendation has been generated and facilitate trust in AI-assisted healthcare systems. Although previous studies have demonstrated the value of machine learning for healthcare prediction and treatment optimization, several limitations remain. Many approaches focus primarily on disease prediction rather than dosage optimization. Other studies provide accurate predictions but offer limited interpretability regarding treatment recommendations. Furthermore, relatively few frameworks integrate patient demographics, clinical measurements, medication history, predictive analytics, and explainability analysis within a unified architecture specifically designed for personalized drug delivery and dosage optimization. To address these limitations, the proposed framework combines machine learning-based dosage prediction with SHAP-based explainability analysis. By integrating predictive capability and interpretability, the framework aims to support individualized treatment planning and evidence-based chronic disease management.

III. PROPOSED METHODOLOGY AND EXPERIMENTAL SETUP

A. Framework Architecture

The proposed Artificial Intelligence-Driven Computational Framework (AICF) is designed to support personalized drug delivery and dosage optimization in chronic disease management by integrating patient-specific clinical information, predictive analytics, and explainable artificial intelligence. The framework combines healthcare data processing, machine learning-based dosage prediction, and interpretability mechanisms within a unified decision support architecture. The objective is to generate individualized dosage recommendations while providing transparent explanations regarding the factors influencing treatment decisions. The overall architecture of the proposed framework is illustrated in Fig. 1.

Fig 1. Architecture of the Proposed AI-Driven Personalized Drug Delivery and Dosage Optimization Framework

The framework consists of five major components: Patient Data Layer, Data Processing Layer, Prediction Layer, Dosage Optimization Layer, and Explainability Layer. Patient-specific information is initially collected and processed to generate meaningful predictive features. A machine learning model subsequently predicts dosage requirements, while an explainability module identifies the clinical variables contributing to recommendation outcomes. The resulting dosage recommendation and explanation report are provided to support clinical decision-making.

B. Dataset Description

The dataset employed in this study consists of patient records obtained from chronic disease management programs. The records include demographic information, physiological measurements, laboratory test results, medication histories, and treatment response indicators. These variables provide a comprehensive representation of patient health status and therapeutic requirements. The dataset contains patients diagnosed with chronic conditions requiring long-term medication management, including diabetes, hypertension, cardiovascular disease, and chronic kidney disease. Each record includes information regarding patient characteristics and observed dosage requirements determined during routine clinical care. The principal clinical variables utilized in the proposed framework are summarized in Table 1.

TABLE 1. CLINICAL FEATURES USED FOR DOSAGE OPTIMIZATION

Feature	**Description**
Age	Patient age

Gender	Patient gender
Weight	Body weight
Blood Pressure	Clinical measurement
Blood Glucose Level	Laboratory measurement
Disease Severity Score	Clinical condition indicator
Medication History	Previous treatment records
Drug Response Score	Observed therapeutic response
Dosage Level	Target variable

The target variable represents clinically recommended dosage levels and is categorized into three groups:

Low Dosage
Moderate Dosage
High Dosage

These categories enable the prediction model to support personalized dosage selection based on patient-specific characteristics.

C. Data Preprocessing and Feature Engineering

Healthcare datasets often contain incomplete records, inconsistencies, and variations arising from differences in clinical documentation and measurement procedures. Therefore, data preprocessing is performed before predictive modeling. Initially, missing values are identified and handled using suitable imputation methods. Numerical variables are processed through mean-value substitution, while categorical variables are treated using mode-based replacement. Duplicate records and inconsistent observations are removed to improve dataset reliability. Following data cleaning, feature normalization is applied to reduce variations in measurement scales among clinical variables. This step ensures that variables with larger numerical ranges do not disproportionately influence model training. Categorical attributes such as gender and disease category are converted into numerical representations using encoding techniques. Feature engineering is subsequently performed to derive additional clinically meaningful indicators. Composite measures representing treatment effectiveness, disease progression, and medication response are generated from original variables. Correlation analysis is employed to identify redundant attributes and reduce multicollinearity. Features exhibiting high redundancy are removed to improve computational efficiency and model stability. The resulting feature set provides a balanced representation of demographic, physiological, and therapeutic information required for dosage optimization.

D. Personalized Dosage Prediction Model

Following preprocessing, the dataset is divided into training and testing subsets using an 80:20 partitioning strategy. The training dataset is used for model construction, while the testing dataset is reserved for independent evaluation. A Random Forest classifier is selected as the primary dosage prediction model because of its ability to handle heterogeneous healthcare data and capture nonlinear relationships among clinical variables. Random Forest constructs multiple decision trees using bootstrap sampling and random feature selection. The final dosage recommendation is obtained through majority voting across individual trees. The prediction model classifies patients into one of three dosage categories:

Low Dosage
Moderate Dosage
High Dosage

Hyperparameter tuning and five-fold cross-validation are performed during model training to improve generalization performance and reduce overfitting. This strategy enhances model robustness when applied to unseen patient records.

E. Explainability Analysis

Interpretability is a critical requirement for healthcare decision support systems because clinicians must understand the factors influencing treatment recommendations. To improve transparency, the proposed framework incorporates an explainability module based on Shapley Additive Explanations (SHAP). SHAP assigns contribution values to individual clinical variables according to their influence on dosage recommendations. Positive contributions indicate factors associated with increased dosage requirements, whereas negative contributions indicate variables supporting lower dosage recommendations.

The explainability module provides both global and local interpretations. Global explanations identify the clinical variables that most strongly influence dosage decisions across the patient population. Local explanations provide patient-specific insights describing the factors responsible for individual dosage recommendations. This capability enables healthcare professionals to understand the rationale behind AI-generated recommendations and supports evidence-based treatment planning.

F. Algorithm of the Proposed Framework

The operational workflow of the proposed framework is summarized in Algorithm 1.

Algorithm 1. Personalized Dosage Optimization Framework
Input: Patient clinical dataset
Output: Personalized dosage recommendation

1. Acquire patient clinical records.
2. Remove incomplete and inconsistent data.
3. Normalize clinical variables.
4. Encode categorical attributes.
5. Extract relevant predictive features.
6. Split dataset into training and testing subsets.
7. Train Random Forest prediction model.
8. Generate dosage recommendation.
9. Apply SHAP explainability analysis.
10. Rank influential clinical variables.
11. Generate decision support report.
12. Return personalized dosage recommendation and explanation.

The algorithm integrates predictive analytics and explainability analysis to provide clinically interpretable dosage recommendations.

G. Experimental Setup

Experimental evaluation was conducted using chronic disease management datasets containing patient demographic information, physiological measurements, medication histories, and treatment outcomes. The dataset was partitioned using an 80:20 train-test ratio. Five-fold cross-validation was employed during model development to improve reliability and reduce performance variability. The framework was implemented using Python-based machine learning libraries. Model performance was evaluated using Accuracy, Precision, Recall, and F1-Score, which provide a comprehensive assessment of classification effectiveness and recommendation reliability. The experimental configuration was designed to evaluate both predictive performance and interpretability. The results obtained from the proposed framework are presented and discussed in the subsequent section.

IV. RESULTS AND DISCUSSION

A. Prediction Performance Evaluation

The performance of the proposed Artificial Intelligence-Driven Computational Framework (AICF) was evaluated using an independent testing dataset to assess its effectiveness in generating personalized dosage recommendations for chronic disease management. Four standard classification metrics—Accuracy, Precision, Recall, and F1-Score—were employed to measure predictive performance. These metrics are widely used in healthcare analytics because they provide a balanced assessment of classification capability and recommendation reliability. The classification performance achieved by the proposed framework is summarized in Table 2**.**

TABLE 2. PERFORMANCE EVALUATION RESULTS

Metric	**Value (%)**
Accuracy	93.4
Precision	92.8
Recall	92.1
F1-Score	92.4

The results indicate that the proposed framework achieved an overall accuracy of 93.4%, demonstrating strong capability in predicting appropriate dosage categories based on patient-specific clinical characteristics. Precision reached 92.8%, indicating a low proportion of incorrect dosage recommendations. Recall achieved 92.1%, suggesting that the model successfully identified the majority of appropriate dosage classes. The F1-score of 92.4% further confirms the balanced relationship between precision and recall. The strong predictive performance can be attributed to the integration of diverse clinical variables, including demographic characteristics, physiological measurements, disease severity indicators, medication history, and observed treatment response. These variables collectively provide a comprehensive representation of factors influencing dosage requirements in chronic disease management.

B. Comparative Analysis

To evaluate the effectiveness of the proposed framework, its performance was compared with several commonly used machine learning algorithms, including Decision Tree, k-Nearest Neighbors (KNN), Naïve Bayes, and Support Vector Machine (SVM). All models were trained and evaluated using the same dataset and experimental conditions to ensure a fair comparison. The comparative results are illustrated in Fig. 2**.** The comparative analysis demonstrates that the proposed Random Forest-based framework achieved the highest classification accuracy among all evaluated approaches. The Decision Tree model achieved an accuracy of 84.9%, while KNN obtained 86.5%. Naïve Bayes produced an accuracy of 82.8%, and SVM achieved 89.2%. In contrast, the proposed framework achieved an accuracy of 93.4%.The improved performance can be attributed to the ensemble learning strategy employed by Random Forest. By combining multiple decision trees, the model effectively captures nonlinear relationships among clinical variables while reducing sensitivity to noise and data variability. This characteristic is particularly important in healthcare datasets, where patient characteristics and treatment responses often exhibit substantial heterogeneity.

The results indicate that ensemble learning approaches are well suited for dosage optimization tasks because they can accommodate complex interactions among demographic, physiological, and therapeutic variables.

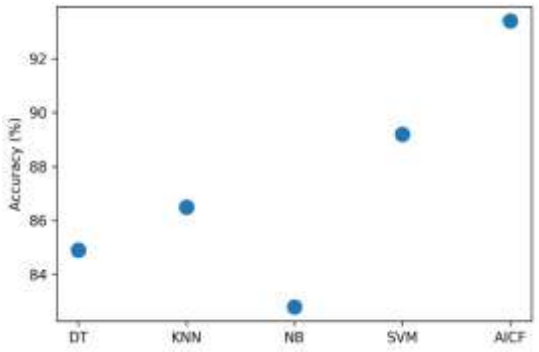

Fig 2. Comparison of Dosage Prediction Accuracy Across Machine Learning Models

C. Explainability Analysis

Although predictive accuracy is an important requirement for clinical decision support systems, transparency and interpretability are equally important. Healthcare professionals must understand the factors influencing treatment recommendations before incorporating AI-generated outputs into patient care. Therefore, SHAP-based explainability analysis was performed to identify the clinical variables contributing most significantly to dosage recommendations. The SHAP-based feature importance analysis is presented in Fig. 3**.**

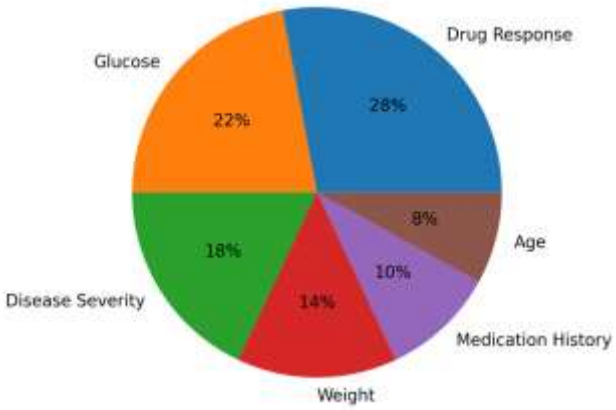

Fig 3. SHAP-Based Importance of Clinical Variables for Dosage Optimization

The explainability analysis revealed that the Drug Response Score was the most influential predictor of dosage recommendations. Patients demonstrating limited therapeutic response to previous treatments generally required higher dosage adjustments, whereas favorable treatment responses were often associated with lower dosage requirements. Blood Glucose Level emerged as another highly influential variable, particularly for patients with diabetes-related conditions. Variations in glucose control significantly affected dosage recommendations and contributed to classification outcomes. Disease Severity Score also demonstrated substantial influence, indicating that patients with more advanced disease conditions frequently required modified therapeutic strategies. Body Weight was identified as an important predictor because dosage requirements often vary according to patient size and physiological characteristics. Medication History contributed significantly to the prediction process as well, reflecting the importance of previous treatment outcomes and therapeutic exposure in determining future dosage

recommendations. Age was also found to influence dosage decisions, consistent with clinical practices that consider age-related physiological changes during medication management. The SHAP analysis provides both global and patient-specific interpretations. Global explanations identify the most influential variables across the entire patient population, while local explanations reveal the factors responsible for individual dosage recommendations. This capability improves transparency and facilitates clinical understanding of model behavior.

D. Discussion

The experimental results demonstrate that the proposed framework effectively integrates machine learning and explainable artificial intelligence to support personalized dosage optimization in chronic disease management. The achieved accuracy of 93.4% indicates that patient-specific clinical data contain sufficient information to support reliable dosage prediction. One important observation is the contribution of treatment response indicators and physiological measurements to dosage recommendations. Variables such as Drug Response Score, Blood Glucose Level, and Disease Severity Score consistently emerged as influential predictors, highlighting the importance of individualized treatment assessment. These findings align with clinical practice, where therapeutic decisions are often based on observed treatment effectiveness and patient health status. The comparative analysis further demonstrates the advantages of ensemble learning techniques in healthcare decision support applications. Random Forest consistently outperformed conventional classifiers, suggesting that ensemble methods are better suited for capturing complex interactions among clinical variables. The ability to model nonlinear relationships contributes to improved prediction reliability and more accurate dosage recommendations. The explainability component represents another significant contribution of the framework. Traditional predictive models often provide recommendations without sufficient explanation, limiting their acceptance in clinical environments. By identifying the factors influencing dosage decisions, the SHAP module improves transparency and supports evidence-based clinical interpretation. Overall, the results indicate that the proposed Artificial Intelligence-Driven Computational Framework provides a practical approach for personalized drug delivery and dosage optimization. The combination of predictive performance and interpretability may assist healthcare professionals in making informed therapeutic decisions while supporting individualized chronic disease management.

V. CONCLUSION AND FUTURE WORK

This paper presented an Artificial Intelligence-Driven Computational Framework (AICF) for personalized drug delivery and dosage optimization in chronic disease management. The proposed framework integrates patient demographic information, clinical measurements, medication history, treatment response indicators, machine learning-based prediction, and explainability analysis within a unified decision support architecture. By utilizing patient-specific healthcare data, the framework aims to support individualized therapeutic recommendations and improve dosage selection processes. A Random Forest classifier was employed to predict dosage categories based on clinical and physiological characteristics. Experimental evaluation demonstrated strong predictive performance across multiple classification metrics, indicating the effectiveness of the proposed approach for personalized dosage optimization. The results showed that integrating diverse clinical variables enables the framework to capture important relationships between patient characteristics and therapeutic requirements. The comparative analysis further demonstrated that the proposed framework outperformed several conventional machine learning approaches, highlighting the advantages of ensemble learning techniques in healthcare decision support applications. An important contribution of this study is the incorporation of SHAP-based explainability analysis. The explainability module identified the clinical variables that most strongly influenced dosage recommendations and provided transparent insights into model decision-making. The findings indicated that treatment response indicators, disease severity measures, physiological measurements, and medication history play significant roles in determining dosage requirements. Such interpretability is valuable for supporting clinician understanding and facilitating the integration of artificial intelligence into healthcare workflows. The results suggest that artificial intelligence-assisted decision support systems can contribute to personalized drug delivery and dosage optimization in chronic disease management. Future work will focus on validating the framework using larger multi-center clinical datasets, investigating deep learning-based prediction models, integrating electronic health record systems, and evaluating the framework across multiple chronic disease categories. Additional studies may explore longitudinal treatment monitoring and prospective clinical validation to further assess practical applicability.

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