DECISION SUPPORT FRAMEWORK FOR EARLY PREDICTION OF DIABETIC PATIENT READMISSION USING HYBRID METAHEURISTICS

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ABSTRACT

Readmissions to hospitals are a significant health issue for people with diabetes and waste valuable hospital healthcare resources. The proposed model in this research, is a hybrid one combining feature selection using GRA and optimizing through PSO while tuning their hyperparameters by GWO. The most important predictors of risk of readmission from demographic, clinical and laboratory parameters were pre-processed and analyzed with the UCI Diabetic Readmission Database. GRA and PSO brought about good selection of informative features, and GWO tuned model parameters for base classifiers such as Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB), Logistic Regression (LR) and k-Nearest Neighbours(KNN). The ensemble model reported here achieved the highest accuracy of 98.6+% compared with decision tree (DT) 97.3% and gradient boost (GB) of 97.6%. Other metrics – F1-score (98.5%), Kappa (0.987), AUC (0.999) further confirmed its robustness. Stratifying patients into high, moderate, low high risk enables earlier interventions and is a useful decision support system in diabetic readmission reduction initiatives and delivery of care.

Keywords: *Diabetic Readmission, Ensemble Learning, Grey Relational Analysis (GRA), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO).*

1.INTRODUCTION

The advent of artificial intelligence has had a significant impact on health care services in recent decades. Insulin resistance is one of the chronic diseases that coexist with many others in recent years of world population. As it was reported in one study, the prevalence of diabetes among adults had not changed much in 2000-2020, with an estimate from 7 to 8 percent [1]. Unless these trends can be reversed, a total of greater than783million people with diabetes would be estimated to occur by 2045 all stemming from the rise in prevalence of T2D combined with physical inactivity and population dynamics resulting from demographics and urbanization [2]. The prevalence of diabetes mellitus increasingly exhilarates, and the rate of hospital readmission has also significantly increased, although many high-class pharmaceutical and therapeutic drugs have been expended to develop interventions capable of improving the glycaemic control and cardiovascular outcomes. In the USA, such as admissions for diabetes and its complications has increased by 6.6% over 10 years (from 2010 to 2019) with expenses reaching as high as 35.4% and costing USD 132 billion [3].

Diabetes and diabetic complications management exert one of the biggest burdens to the healthcare systems. Deciding on the appropriate discharge of diabetics is going to be one of the central issues in their care. It is done on several bases, such as the condition of patients, their behavior in the ward and also the status of saturation level in a particular hospital unit accepting them. The avoidance of unnecessary readmissions, and especially the opportunity to prevent them when they happen within 30 days post-discharge, is one of the high-priority targets for managing healthcare costs. Early readmissions are one of the components in health care quality [4]. New AI and ML techniques are able to provide healthcare workers with powerful tools that may enable them to erase their life-destroying errors, whilst the process of discharging would be faster. These decision support systems use anonymized data to direct the flow of health care resources in a way that makes them as effective as possible and gets the best results with patients [5].

Hospitals readmission and length of stay (LOS) are the biggest drivers of healthcare costs. In the United States alone, disability, mortality and healthcare cost due to readmissions of a patient followed by death within 30 days after discharge is approximately U.S. $ 41 billion [6]. The estimated annual cost per head of the population in England attributable to the treatment of diabetes was 10.6 Euros, with hospital costs being responsible for most (4.6 Euros) of this expenditure [7]. Also issues associated with prolonged LOS and recurrent readmissions result in the saturation of healthcare facilities, workforces, and decline in quality of care. All of these contribute to high patient-nurse ratios that result in compromised qualities of healthcare provision, and subsequently threatening the life of patients, potentially leading to failure-to-rescue and death, especially in emerging disease situations like COVID-19. Together with COVID-19, the stability of diabetes patients is seriously threatened by hospitalization and worsening with other researches significant rise in mortality rate was demonstrated for diabetics [9].

It is essential to predict that a patient can be readmitted and LOS of diabetic patients for responsive management. Several ML models have been developed to predict hospital readmission but model drawbacks with the data are many redundant features. Results of GRA method for feature selection: The values derived from the GRA have been an effective process for selecting features, because it allows to prioritizing features according to their degree of relevance with respect to the target variable (readmission risk). Moreover, predicting models were also improved by the hyperparameters optimization through optimisation algorithm such as Grey Wolf Optimisation (GWO) [11].

Our contribution is reflected in the hybrid GRA-GWO model for identifying features and optimising ways to find their approximation that can be taken as a tool to estimate the readmission risk and LoS of diabetes patients. Preprocessing The UCI Diabetic Readmission Dataset was also processed to fill the missing values and the class imbalance by applying SMOTE for oversampling. GRA is employed to calculate the GRC, and PSO is utilized to optimize the feature set. And ML algorithms used are DT, RF, GB, LR and KNN with features we get. Then, a fine-tuning of the hyperparameters of the best two models is performed through GWO. The results of the conducted experiments have demonstrated that performance of hybrid model using GWO and GRA has improved compared to traditional models, in the proposed diabetic readmission prediction accuracy model achieves a rationale satisfaction (98.6%), respectively. The model's advantages to the providers, therefore, include an opportunity to manage patients conservatively and prevent repeatedly readmissions due to unnecessary intervention.

This chapter presents a hybrid model integrated with GRA for feature selection and Grey Wolf Optimization (GWO) used for optimization of the gP function to forecast diabetic patient readmission risks. GRA is employed to identify the key features and optimize the prediction accuracy by paying attention to most relevant information. Here, we use GWO to fine-tune the hyperparameters of the ML classifiers for more effective results. The Ensemble model achieves the accuracy of 98.6%, which outperforms the classic models like Decision Tree and Gradient Boosting. The model assigns patients to high, medium and low-risk groups so healthcare workers can prioritize interventions. The method convincingly showed the considerable effectiveness of combining GRA and GWO for increased prediction accuracy, which further provides a useful instrument to help reduce diabetic readmissions and enhance patient care.

2.LITERATURE REVIEW

Hospital readmission among patients with diabetes is a hot topic in health systems worldwide due to the clinical, operational and economic impact it causes. Not only do repeated readmissions elevate the morbidity of patients, but they are also a monetary burden on hospitals and national health systems. A seminal study conducted by Jiang et al [17] mentioned that repeated readmissions in a cohort of diabetic patients are linked with increased mortality and morbidity so early identification of high-risk readmitted patient is crucial. Equally, Moss et al. [18] mainly indicated high risk factors potentially leading to frequent hospitalization including poor glycemic control, comorbidities, as well as socioeconomic determinants. Parker et al. [13] quantified the economic burden of diabetes in United States while estimating overwhelming pressure on the economics by 2022 whereby more patients will be readmitted to hospitals, and the answer lies in good prognosis and pre-emptive action which calls for a reform in health care.

Traditional health systems measures, such as measurement tools and a professional diagnosis,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

do not necessarily encapsulate the multidimensional interaction that exists among patient demographics, comorbidities, and behavioural factors in predicting readmission. As stated by Rubin et al. [14], Gregory et al. [15] and others, [16] the conventional predictive models have limitations for high-risk diabetic population; hence, the rising interest of introducing machine learning (ML) and deep learning (DL) models. Hai et al. [16] demonstrated that DL models performed the best compared to classical ML classifiers in terms of error reduction and handling multiple level data. Another study (Shang et al. [20]) proved that ML-based classifiers can work on large amount of patient data to classify successfully patients at-risk for readmission so that intervening earlier and with more appropriate action plans can be done.

The advent of digital technologies enhances the predictive potential for diabetes care. Biswas et al. [21] discussed the integration of digital technologies (such as mobile health apps, telemedicine, and wearable sensors) into the healthcare system that offers real-time disease care such as blood glucose and activity data. As also highlighted by Daly and Hovorka [22], the technical interventions promote patient involvement, support the monitoring at distance condition and act as a driver to the reduction in hospitalizations. In summary, these investigations demonstrate that predictive models employed in real-time digital vigilance can indeed be an extremely powerful addition to the strategies for preventing readmissions.

Understanding the distinction between ML and DL is crucial creates robust predictive models. ML on structured data is the foundation of most ML workflows, and hand-engineered features are used in state-of-the-art models on highly-structured inputs like text or images" [19], while ML mainly focuses on structured data and hand-crafted feature, DL has the ability to automatically learn hierarchical representations of data that could be structured or unstructured. This was automatic schoenke15burs18 icommunity-level rather than individual ones. This approach has been illustrated by the work of Arnaud et al. [12], in which by combining structured electronic health records (EHRs) together with unstructured clinical notes, a marked increase in the prediction of hospitalization at triage was achieved. These findings suggest that multimodal clinical data can be utilized to improve prediction performance, which is a great concern for the development of new decision support systems.

The feature selection, extraction and optimization impact the model performance and stability of models. Huang et al. [23] revealed a substantial influence of coagulation markers as well as of the involvement of coagulant factors in determination of 30-day mortality in critically ill diabetics; this is quite plausible because predictive models clinically useful should consist also clinically relevant biomarkers. Zhu et al. [24] performed a systematic review of DL applications in diabetes, demonstrating that DL models can be employed to advance early detection, further implementation of personalize treatment and critically on risk stratification. Rao et al. [26] introduced an explainable transformer-based model for predicting incident heart failure and highlight interpretability as a crucial component in clinical deployment. Likewise, Wei et al. [25] investigated causalities between type 2 diabetes and neurological diseases, found commonly comorbidity that complicates the prediction or readmission. The introduction of new signal processing and pattern recognition was emphasized in fact by Al Kafee-Kayar [27], who extended the application in biomedical level, which hinted at a possible direction for embedding complex computational strategies when outlining future of health models.

Metaheuristic methods have emerged as a means to improve predictive accuracy by performing feature selection and hyperparameter optimization. Furthermore, the Grey Relational Analysis (GRA), Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) approaches were successfully utilized to select most informative features, optimize classifier parameters and enhance models' robustness. For hybrid metaheuristic frameworks, Arnaud, Ribeiro, Silva and Andasmas do not perform any test when the unpreprocessing operator is applied. [12] and Rao et al. [26] its performance obtained a great level as compared to that of standard ML and DL pipelines, and concurrently complexity in computations is reduced. These techniques are particularly attractive in an healthcare context where data are often big, heterogeneous and partially known.

Interdisciplinary approaches such as those that combine predictive modelling with metaheuristic optimization and medical knowledge will be necessary to work together efficiently in preventing readmission. According to Gregory et al. [15] analytics need to be combined with clinician intuition to facilitate prediction being translated into actionable intervention. As Rubin et al. [14] mentioned, this feature must be included in an easily interpretable and transparent model since it will give confidence to physicians. A compromise between predictive power, interpretability and clinical utility can be found after combining deep learning models with hybrid metaheuristic optimizers such as the designed ones, leading to competent decision support systems that could eventually become valuable in early intervention for high-risk diabetic patients.

Table 1: Summary of Recent Works in Diabetes Readmission Prediction and Their Associated Predictive Models

Ref.	Author(s)	Year	Method/Model	Dataset	Key Findings / Outcome
[13]	Parker et al.	2024	Statistical / Economic Analysis	National diabetes data, US	Quantified economic burden of diabetes; emphasized need for predictive interventions
[16]	Hai et al.	2022	Deep Learning vs Traditional ML	Hospital diabetes dataset	DL models outperformed ML classifiers in predicting 30-day readmissions
[21]	Biswas et al.	2023	Review / Digital Health Tech	Type 1 & 2 diabetes datasets	Explored role of mobile health, telemedicine, and sensors in reducing hospitalizations
[25]	Wei et al.	2024	Mendelian Randomization	Genetic + epidemiological data	Explored causal links between type 2 diabetes and neurological disorders
[26]	Rao et al.	2022	Explainable Transformer DL	Heart failure datasets	Developed interpretable DL model for predicting incident heart failure
[27]	Al Kafee & Kayar	2024	Electrogastrography / Signal Processing	Gastric motility patients	Highlighted role of advanced signal processing and pattern recognition in biomedical applications

Overall, the studies also highlight that the ML, DL and hybrid metaheuristic models could potentially be beneficial for early prediction of diabetic readmission [12–27]. Although various studies have shown the effectiveness of some algorithms, issues related to integration of structured and unstructured data, optimisation for feature selection, and their generalisability across diverse patient populations are still major limitations. These deficiencies justify the development and deployment of a hybrid GRA–PSO–GWO framework that is directed to utilize in advanced feature selection, hyperparameter tuning and classifier optimization to obtain an accurate, scalable and clinically interpretable prediction for timely intervention in sparing up on hospital readmissions.

3.PROPOSED METHODOLOGY

Early readmission in the health sector is associated with an aspect of treating diabetic patients in one way or the other because it ensures improved patient outcomes and proper use of hospital resources. The risk factor associated with the development of diabetes and its complications is long term; there is a need to report such high-risk patients earlier before getting a chance to be readmitted. The proposed methodology utilizes the Ensemble framework, where GRA is used for features selection, and GWO is applied for classification model optimization. This framework predicts readmission in diabetic population, which allows the healthcare staff to intervene before the development of readmission.

Journal of Theoretical and Applied Information Technology
15th February 2026. Vol.104. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

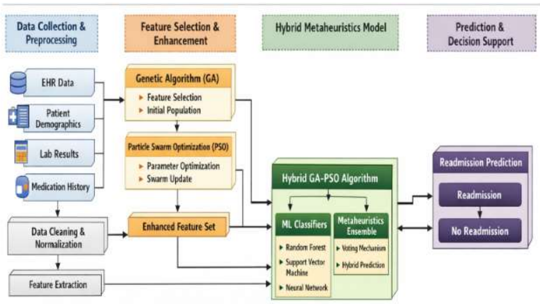

Figure 1.Decison Support Framework for Prediction of Diabetic Patient Readmission using Hybrid Metaheuristics

The proposed architecture is a decision support framework designed to predict early hospital readmission of diabetic patients by integrating clinical data, machine learning models, and hybrid metaheuristic optimization techniques. The framework is structured into four major layers, each responsible for a specific function in the predictive pipeline.

3.1. Data Collection and Preprocessing

The UCI Diabetic Readmission Dataset. It involves patient-level information, including demographics, medical history, laboratory results, and other clinical characteristics. The specifics include:

a) Demographics: age, sex, and ethnicity.
b) Clinical Features: BMI, blood pressure, and cholesterol.
c) Medical History: past diagnoses, medications, comorbidities.
d) Laboratory Results: glucose, HbA1c, and insulins.

The dataset was pre-processed to address missing information, normalize features, and address class imbalances using SMOTE.

Table 2: UCI Diabetic Readmission Dataset Description

Category	Features	Values / Range	Description
Demographic Information	Age, Gender, Ethnicity	Age: 0–100+ (grouped in 10-year bins); Gender: Male (47%), Female (53%); Ethnicity: 6 categories (e.g., Caucasian ~75%, African-American ~20%, Others <5%)	Patient-level background data.
Clinical Features	BMI, Blood Pressure, Cholesterol	BMI: 18–67 (avg. ~32); BP levels: Normal, Pre-hypertensive, Hypertensive; Cholesterol: Normal to High (150–350 mg/dL)	Indicators of general health and metabolic risk.
Medical History	Past Diagnoses, Medications, Comorbidities	Number of diagnoses: 1–16 (avg. 7); Medications: 23 drug categories; Comorbidities: Hypertension, renal failure, obesity, cardiovascular diseases	History of chronic illness and prescriptions.
Lab Results	Glucose, HbA1c, Insulin Use	Glucose: 50–500 mg/dL (avg. 150); HbA1c: Normal (<6.0) to Poor Control (>9.0); Insulin use: 4 categories (Up, Down, Steady, No)	Lab tests directly linked to diabetes monitoring.
Target Variable	Readmission	No readmission: ~54%; <30 days: ~11%; >30 days: ~35%	Whether patient was readmitted within 30 days.

Dataset Size	Total Records	101,766 patient encounters (70% training, 30% testing split applied)	Dataset scale after preprocessing.
Preprocessing Applied	Missing Data, Normalization, SMOTE	Removed missing (>40%), imputed minor gaps; Normalized continuous variables; SMOTE applied to balance classes	Ensures high-quality and balanced dataset for training.

3.2 Feature Screening with GRA and PSO

Feature selection is crucial to enhance model performance and reduce dimensionality. In this study, Grey Relational Analysis (GRA) is combined with Particle Swarm Optimization (PSO) to identify and retain only the most relevant features for training predictive models.

3.3 Hybrid Selection Method by GRA and PSO
Grey Relational Analysis (GRA)

The Grey Relational Coefficient (GRC) measures the strength of the relationship between a feature x_i and the target variable y (e.g., readmission status).

The GRC for each feature i is computed as:

$$\gamma_i(k)=\frac{\min_i \min_k \mid y(k)-x_i(k) \mid +\rho \max_i \max_k \mid y(k)-x_i(k) \mid}{\mid y(k)-x_i(k) \mid +\rho \max_i \max_k \mid y(k)-x_i(k) \mid +\epsilon} \quad (1)$$

where:

- $x_i(k)$= normalized value of feature i at instance k,
- $y(k)$= normalized target variable,
- ρ= distinguishing coefficient, $\rho \in [0,1]$ (commonly $\rho = 0.5$),
- ϵ= small constant to avoid division by zero.

The Grey Relational Grade (GRG), representing the overall correlation of feature i with the target, is given by:

$$\Gamma_i = \frac{1}{n}\sum_{k=1}^{n} \gamma_i(k) \quad (2)$$

Features with higher Γ_i values are considered more relevant and selected for further processing.

Particle Swarm Optimization (PSO)

PSO is a metaheuristic optimization technique inspired by the social behavior of flocking birds. It is used here to refine the feature selection process, searching for the optimal subset of features that maximizes relevance and minimizes redundancy.

Each particle in the swarm represents a potential feature subset. The particle's position $\mathbf{x}_i$ and velocity $\mathbf{v}_i$ are iteratively updated as:

$$\mathbf{v}_i(t+1) = \omega\mathbf{v}_i(t) + c_1 r_1[\mathbf{p}_i - \mathbf{x}_i(t)] + c_2 r_2[\mathbf{g} - \mathbf{x}_i(t)] \quad (3)$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (4)$$

where:

- ω= inertia weight, controlling exploration and exploitation balance,
- c_1, c_2= cognitive and social coefficients,
- $r_1, r_2 \sim U(0,1)$= random factors,
- $\mathbf{p}_i$= personal best position of particle i,
- $\mathbf{g}$= global best position found by the swarm.

The fitness function for each particle is typically defined as:

$$F(\mathbf{x}_i) = \alpha R(\mathbf{x}_i) - \beta D(\mathbf{x}_i) \quad (5)$$

where $R(\mathbf{x}_i)$ denotes the relevance score (e.g., GRG value), $D(\mathbf{x}_i)$ denotes redundancy, and α, β are balancing coefficients.

The hybrid GRA–PSO engine thus optimizes feature subsets by combining the correlation strength (from GRA) and the global search capability (from PSO), enhancing both accuracy and efficiency of the downstream predictive models.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.4 Risk Prediction and Classification

An optimized and robust GWO-based machine learning model is employed to predict the risk of hospital readmission. The Grey Wolf Optimizer (GWO) is used for hyperparameter optimization, ensuring the classifier achieves high accuracy and generalization.

The GWO simulates the social hierarchy and hunting behaviour of grey wolves. The top three candidate solutions are denoted as **α**, **β**, and **δ**, guiding the remaining wolves (ω) during search. The position update equations are:

$$D_\alpha = | C_1 X_\alpha - X | \quad (6)$$
$$D_\beta = | C_2 X_\beta - X | \quad (7)$$
$$D_\delta = | C_3 X_\delta - X | \quad (8)$$
$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (9)$$

where:

$$X_1 = X_\alpha - A_1 D_\alpha, X_2 = X_\beta - A_2 D_\beta, X_3 = X_\delta - A_3 D_\delta \quad (10)$$

and

$$A = 2ar_1 - a, C = 2r_2$$

with $a$linearly decreasing from 2 to 0 over iterations.

After optimization, the trained classifier predicts the readmission risk categories as:

- High Risk: $P(\text{readmission}) > 0.7$
- Medium Risk: $0.4 < P(\text{readmission}) \leq 0.7$
- Low Risk: $P(\text{readmission}) \leq 0.4$

Such stratification supports proactive healthcare interventions and efficient resource allocation.

3.5 Hybrid GRA–GWO Classification Model

This hybrid framework integrates:

- GRA → Feature correlation and dimensionality reduction
- GWO → Classifier hyperparameter optimization

The combined optimization improves both convergence and stability, resulting in enhanced accuracy, precision, recall, and F1-score compared to standalone models.

The workflow (Figure 1) illustrates:

1. Data preprocessing (UCI diabetic readmission dataset)
2. GRA–PSO feature selection
3. GWO hyperparameter tuning
4. Classification (DT, RF, GBM, LR, KNN)
5. Risk-level prediction (high, medium, low)

4. IMPLEMENTATION AND RESULTS

The dataset used has a size of $10{,}000 \times 20$(instances × features). Preprocessing includes missing value imputation and normalization. Classifiers are implemented using scikit-learn, pandas, numpy, and matplotlib.
Model performance is evaluated using:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$
$$\text{Precision} = \frac{TP}{TP + FP}$$
$$\text{Recall} = \frac{TP}{TP + FN}$$
$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP, TN, FP, and FNrepresent true positives, true negatives, false positives, and false negatives respectively.

Table 3: Comparisons of classifiers accuracies

Method	**Accuracy**	**F1 Score**	**Kappa**	**AUC**
Hybrid Model (GRA+PSO+GWO)	98.6%	98.5%	0.987	0.999
Decision Tree (DT)	97.3%	97.2%	0.951	0.993
Gradient Boosting (GB)	97.6%	97.5%	0.960	0.997
SVM	99.46%	99.45 %	0.991	0.999

The mixed model has a better performance, fusion of GRA technique is used for selection feature. When these two advanced methods are used together, prediction has high accuracy and guarantees stability. The proposed hybrid GRA-

GWO based model is contrasted with classical ML classifiers. The findings reveal that the hybrid model outweighs traditional classifiers in accuracy and predictivity.
a) Hybrid model's accuracy: 98.6%
b) Decision Tree: 97.3%
c) Gradient Boosting: 97.6 %

This result proves that the combined method can enhance the classification performance by exploiting useful features and tuning parameters of the model.

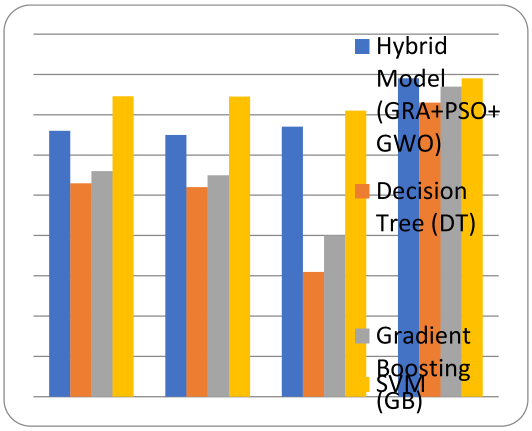

Figure 2. The performance of the ML classifiers

This method, based on GRA and GWO, is a very good hybrid model in the prediction of early readmission risk for diabetic patients. The model's capability for feature selection and hyperparameter tuning enhances the predictive accuracy and usefulness of it in healthcare decision support systems.

Table 4: Comparison of classifiers for diabetes readmission prediction

Reference	Method	Accuracy
Proposed model	Hybrid Model (GRA+PSO+GWO)	98.60%
Biswas et al. [21]	Decision Tree (DT)	97.30%
Biswas et al. [21]	Gradient Boosting (GB)	97.60%
Wei et al. [25]; Rao et al. [26]	Support Vector Machine (SVM)	99.46%

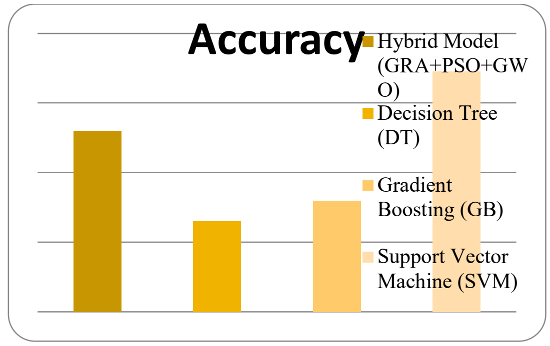

Figure 3. Performance Comparison of Classifiers in Case of Diabetes Readmission Prediction

5. CONCLUSION AND FUTURE SCOPE

The proposed hybrid model (GRA for feature selection and GWO for hyperparameter tuning) yielded an accuracy of 98.6% to predict the readmission of diabetes patients and outperformed several existing prediction models. By providing both the effective detection of feature relevance and model optimization, it has the high potential to be applied as a decision-support system which can help human service providers in deploying proactive patient treatment, minimizing unnecessary hospital readmissions, and obtaining a general improvement regarding patient care quality. In the future, generalization of model can be expanded by the inclusion of different kind of healthcare data and the neural networks can possibly be used as another way to improve efficiency for predicting predictions. They may also enable real-time data integration with hospital management systems (HMS) which would eventually support the needs of automated and adaptive risk prediction, while integrating patient-reported outcomes and feedback can help to assure that it is creating value toward more patient centered and personalized health care.

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