Original Article

Machine Learning Algorithms for Predicting the Impact of Care Burden on the Psychological Well-being of Caregivers for Chronic Kidney Disease Patients

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Abstract

Background: The aim of this study was to apply Machine Learning (ML) algorithms to predict the impact of care burden on the psychological well-being of caregivers of patients with Chronic Kidney Disease (CKD). **Materials and Methods:** This cross-sectional study employed an ML approach to analyze data from 200 primary family caregivers of CKD patients undergoing hemodialysis. The caregivers were selected through convenience sampling from hospitals affiliated with Mashhad University of Medical Sciences. Caregivers completed the demographic form, the Novak and Guest Pressure Care Questionnaire, and Ryff's Scales of Psychological Well-being. Four ML algorithms: Random Forest (RF), logistic regression, decision tree (DT), and Support Vector Machine (SVM) with Linear, Polynomial, and Sigmoid Kernels, were evaluated using Python and the Scikit-Learn module in the Anaconda environment. **Results:** The RF model achieved the highest accuracy score of 0.70, followed by the polynomial SVM model with 0.68. The SVM linear model scored 0.62, logistic regression and DT models both scored 0.58, and the SVM sigmoid model had the lowest accuracy score of 0.54. The RF algorithm also achieved superior levels of the Area Under the Curve (AUC) (0.72) and sensitivity (0.72%). Eight key predictors of psychological well-being were identified: caregiver burden, age, education, economic situation, number of care days, family members, dialysis days, and the amount of assistance offered by family members to the caregiver. **Conclusions:** The RF algorithm, a robust ML tool, effectively analyzed datasets to reveal insights into the relationship between caregiver burden and caregiver well-being in CKD patients.

Keywords: *Algorithms, chronic kidney disease, machine learning, psychological well-being, random forest*

Introduction

Chronic Kidney Disease (CKD) is one of the major health problems in the world, and its common treatment method in Iran is hemodialysis.[1] More than 1 in 7 US adults—about 35.5 million people, or 14%—are estimated to have CKD. CKD is more common in people aged 65 years or older (34%) than in people aged 45–64 years (12%) or 18–44 years (6%).[2] In Iran, the prevalence of this disease is estimated to be between 1200 and 1600 people per year.[3] Many changes occur as a result of this disease, particularly due to the constant need for hemodialysis and reduced energy levels, which can significantly impact the daily activities of patients.[4] The chronicity of the disease affects the whole family.[5] Family caregivers are responsible for providing care and support in the health, social, emotional, and financial fields of patients with chronic diseases. Also, taking care of people who have an advanced form of this disease may have serious consequences for family caregivers.[6,7] Changes in the health status of patients can lead to a wide range of physical, social, and emotional consequences for family caregivers.[8] Studies have shown that this care can have negative effects on the caregiver's health, including sleep problems, frequent headaches, and weight loss or weight gain.[9] Based on the study of Mashaikhi *et al*. (2015), 72.5% of family caregivers of patients with chronic kidney failure reported moderate to severe care burden.[10] Zarit (1980) defines care burden as physical, psychological, social or financial reactions that may occur following the provision of care.[11] According to Winefield *et al*. (2012),[12]

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the concept of psychological well-being is defined as a combination of positive emotional states such as happiness and performance with optimal effectiveness in personal and social life. The study by Mahmoud Mohammed SF and Abdel Hady Ghaith (2018)[13] in Egypt found a negative relationship between caregiver burden and the psychological well-being of family caregivers of mentally ill patients. However, Chappell's study (2002) showed that the quality of life of caregivers can be improved despite the care burden in life.[14] Since chronic diseases can affect different dimensions of caregivers' lives[15] and nurses are in a position to design interventions to help caregivers that can guarantee psychological well-being for caregivers. Therefore, it is necessary to evaluate the caregiver burden to determine the level of support caregivers require.[16]

The incorporation of Information and Communication Technology in healthcare has completely transformed the management of chronic diseases, enabling accurate prediction and informed decision-making. The impact of this on the quality of patient care and the reduction of costs is considerable. Data mining algorithms provide exceptional performance in disease prediction, diagnosis, cost reduction, and real-time decision-making, resulting in life-saving outcomes.

This study examined four sample ML algorithms: RF, logistic regression, DT, and SVM (linear, polynomial, sigmoid) to predict the well-being of caregivers of CKD patients. Preprocessed dataset was subjected to six machine learning (ML) algorithms to construct prediction models, with accuracy serving as the criterion for evaluating these models.[17,18] The RF algorithm is an ML method used when researchers have more predictors than observations. It uses ensemble learning theory to learn simple and complex classification functions accurately. RF does not require fine-tuning of parameters and default parameterization often leads to excellent performance. The SVM can learn complex classification functions efficiently and employs regularization principles to avoid overfitting. SVM linear is used for handling large data vectors, while SVM polynomial is used for processing images and avoiding overfitting. SVM sigmoid is primarily used as a proxy for neural networks. These algorithms were utilized in a comparable investigation.[19] Moreover, it is essential to analyze different algorithms in ML because of the distinctive characteristics of data, since specific algorithms offer higher accuracy and speed.[20,21] These reviews help to address the problems of overfitting and underfitting and make it easier to select models that are more interpretable.[22] Nursing researchers face a hurdle in choosing a suitable prediction model.[23] This study provides a comprehensive analysis of various ML algorithms, including a rationale for their selection. The aim of this study was to use ML algorithms to predict the impact of care burden on the psychological well-being of caregivers of CKD patients. Each algorithm was assessed using core metrics such as accuracy, sensitivity, specificity, positive predictive values, negative predictive values, and the receiver operating characteristic (ROC) curve.

Materials and Methods

The present quantitative cross-sectional study aimed to identify an effective and predictive algorithm for detecting the association between care burden data and the psychological well-being of caregivers of CKD patients. In this study, four questionnaires were utilized, namely: the demographic information questionnaire, the World Health Organization-Five Well-being Index (WHO-5),[24] the Novak and Guest Pressure Care Questionnaire,[25] and the Ryff's Scales of Psychological Well-being.[26]

The World Health Organization-Five Well-being Index (WHO-5) is a self-reported, five-item scale that measures positive well-being over the past two weeks using a 5-point Likert scale, ranging from 0 (never) to 5 (all the time). The raw score theoretically ranges from 0 (no well-being) to 25 (maximum well-being), with higher scores indicating better well-being. In Iran, Dehshiri and Mousavi reported very high internal consistency for the WHO-5, with a Cronbach's alpha of 0.89 and a test-retest reliability coefficient of 0.82.[24]

The Novak and Guest Pressure Care Questionnaire is designed to measure both objective and subjective caregiving pressures (care burden), with a stronger emphasis on measuring subjective caregiving pressure. This questionnaire consists of five subscales: Time-dependent caregiving pressure, developmental caregiving pressure, physical caregiving pressure, social caregiving pressure, and emotional caregiving pressure, which are assessed using a 5-point Likert scale. Caregivers respond to each item with a score ranging from 1 ("completely incorrect") to 5 ("completely correct"). The total score can range from 24 to 120. The questionnaire demonstrates good reliability, with a Cronbach's alpha coefficient of 0.80 for the entire questionnaire.[25] In Iran, Abbasi *et al*.[23] calculated a Cronbach's alpha coefficient of 0.90 for the overall scale.

Ryff's Scales of Psychological Well-being, in its 18-item version, consists of six factors. The total score for these six factors is calculated as an overall score of psychological well-being. This assessment is a self-report instrument where respondents rate their agreement on a 6-point Likert scale ranging from "strongly agree" to "strongly disagree" (1 to 6), with higher scores indicating better psychological well-being. Among all the questions, 10 are directly scored and 8 are reverse-scored. The correlation between the short version of Ryff's Psychological Well-being Scale and the original scale ranges from 0.70 to 0.89.[26]

The primary data collected for this study included various demographic information of the caregivers such as age, gender, education, marital status, occupation, place of residence, economic status, and their relationship with the patient. Additionally, data on the number of family members involved in caregiving, the number of dialysis days, the number of care hours per day, the quantity of assistance offered by family members to the caregiver in relation to caregiving tasks (helper), caregiver burden, and the psychological well-being of the caregivers were collected.

The variable of psychological well-being of caregivers of patients was chosen as the outcome variable for this study. To classify this variable, it was divided into two categories: low psychological well-being and high psychological well-being. This categorization was based on expert opinions, with the mean score serving as the threshold. Scores equal to or below the mean were assigned a value of 0, indicating low psychological well-being, while scores above the mean were assigned a value of 1, indicating high psychological well-being. To assess the convergent validity of this classification with Ryff's Scales of Psychological Well-being, 100 participants completed the (WHO-5) alongside it. Subsequently, the correlation between the scores of these two scales was computed. The results indicated a significant positive correlation ($r = 0.59$, $P < 0.01$), demonstrating convergent validity and suggesting that this classification can effectively differentiate between levels of well-being categorized as 0 and 1.

This study investigates the relationship between care burden data and the psychological well-being of primary family caregivers of patients with CKD who are receiving hemodialysis at hospitals associated with Mashhad University of Medical Sciences. The sample size was estimated using the appropriate formula for correlational studies. For this purpose, the correlation coefficient between caregiving stress and the psychological well-being of caregivers from Mohammad's study (2018) was used ($r = 0.45$). Taking into account a 99% confidence level and a 90% statistical power, the sample size was calculated to be 67. However, for greater accuracy and reliability, a total of 200 participants will be considered.[13] The dataset was collected between 2021 and 2022. Eligibility criteria included informed consent, the absence of mental disorders, no use of psychotropic medications, the ability to read and write, being 18 years of age or older, and having at least 3 months of caregiving experience. The study excluded caregivers who declined to participate. Following the acquisition of consent and ethical approval, the dialysis departments were visited to do convenient sampling. Subsequently, the primary family caregivers were provided with personal information forms, the Novak and Guest Pressure Care Questionnaire,[27] and the Ryff's Scales of Psychological Well-being[25] for completion.

The Python programming language, specifically the NumPy and Pandas libraries, was employed within the Anaconda environment to perform descriptive statistical analyses on the attributes of the caregivers involved. The proposed architecture, as shown in Figure 1, provides a comprehensive overview of this approach. Figure 2 illustrates the two steps of the workflow in this study: feature selection and data preprocessing. The preprocessing consists of four steps: data cleaning, attribute selection, target role definition, and feature extraction. Due to the dataset containing 48 independent variables, testing every combination of variables was not feasible. The features selected by the Random Forest (RF) algorithm are listed in Table 1. Table 1 presents the link between 12 parameters, ascertained by ML, and the state of well-being. By employing RF methods, we identified eight characteristics that strongly predict well-being. The variables encompassed in this study are caregiver burden, age, education, economic status, number of care days, family members, dialysis days, and the level of assistance provided by family members to the caregiver for caregiving tasks.

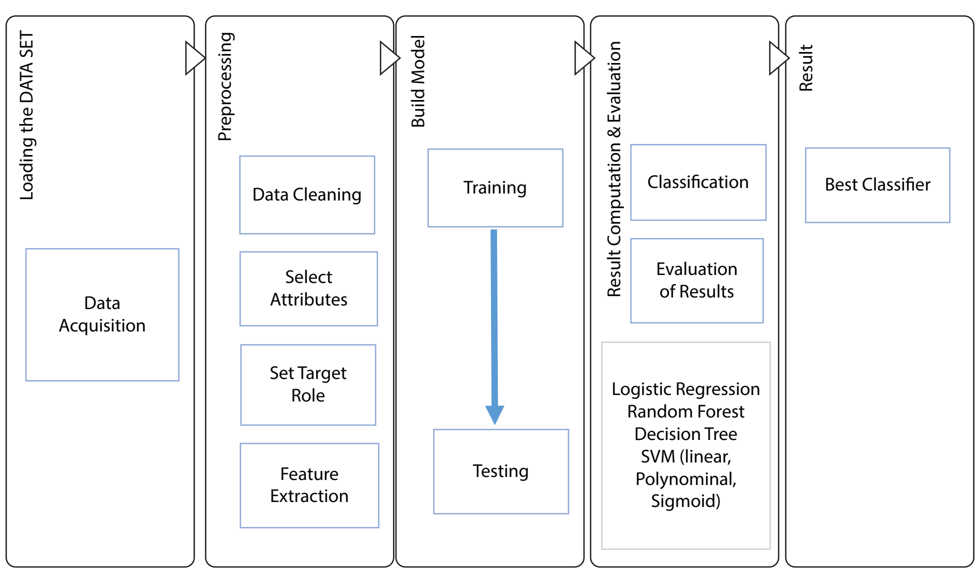

Figure 1: Process Flow Diagram: Detection of Psychological Well-being in Caregivers of Chronic Kidney Disease Patients Using Machine Learning Algorithm

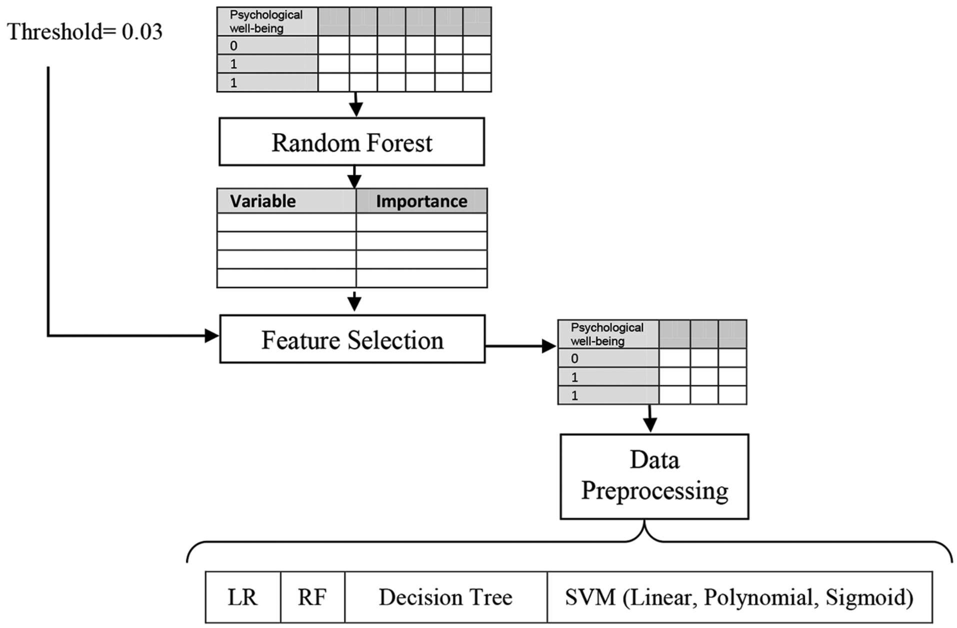

Figure 2: Process of data analysis

Table 1: Predicting Variables of Six Models

Models	CB	Age	Number of care days	Number of care hours per day	Number of family members	Number of dialysis days	Education	Economic situation	Helper	Female	Urban	Married	Total
Logistic regression						*	*	*	*	*	*		6
Random forest	*	*	*		*	*	*	*	*				8
SVM** linear							*	*		*	*	*	5
SVM polynominal	*	*	*										3
SVM sigmoid	*	*	*	*	*								5
Decision Tree	*	*			*		*						4
Total	4	4	3	1	3	2	4	3	2	2	2	1	

*This symbol and gray background indicate that those variables have been identified in the algorithm. **Support Vector Machine (SVM)

Logistic regression identified six predictors, whereas SVM linear and SVM sigmoid identified five predictors each, and decision tree (DT) identified four predictors. The SVM polynomial model, however, only found three predictors. Utilized the RF algorithm to detect and eliminate irrelevant factors, leading to a decrease in the number of independent variables to 19. The data preprocessing stage applied standardization techniques to normalize the values, ensuring the dataset was suitable for ML algorithms. Applied four advanced ML algorithms, specifically RF, logistic regression, DT, and SVM using linear, polynomial, and sigmoid kernels. The techniques were applied to a preprocessed dataset to construct a predictive model. The analysis was conducted using the Python programming language and the Scikit-learn library within the Anaconda environment.

The variable "well-being" was selected as the dependent variable. This variable involves categorizing caregivers into two groups based on their well-being: a group with low well-being (labeled as 0) and a group with strong well-being (labeled as 1). The present study included 48 independent variables. Due to the complexity of the variables, it was not feasible to create a model that could evaluate every potential combination. Therefore, RF was utilized to identify pertinent components, allowing for the computation of relevance ratings for each variable. Table 2 presents a collection of significant variables organized in a decreasing order based on relevance ratings that are higher than 0.03. After speaking with a statistics specialist, the threshold score of 0.03 was chosen as the most suitable option as there are no defined scientific criteria for selecting the threshold score.

During the data preprocessing step, irrelevant variables were discarded, and the remaining variables were processed for compatibility with the analysis. Variables such as patient code, evaluation time, and hospital name, which were deemed unrelated to predicting the psychological well-being of caregivers, were removed. For categorical variables, normalization was performed by encoding values into integers that reflect grades. This was achieved using

Table 2: Description of variables

Variable Importance	Score
Care burden	0.26
Education	0.13
Helper*	0.12
Number of dialysis days	0.08
Age	0.07
Number family members	0.05
Number of care days	0.04
Economic situation	0.04
Urban	0.03
Number of care hours per day	0.03

*The quantity of assistance offered by family members to the caregiver in relation to caregiving tasks

techniques such as Label Encoding or One-Hot Encoding. For instance, the variable "amount of help of family members to the caregiver (helper) was normalized using Label Encoding. The values "high," "moderate," "low," and "never" were assigned integers 3, 2, 1, and 0, respectively. The assumption was that "high" indicated the best score, while "never" represented the worst score. A value of zero was assigned when no evaluation was performed. However, the variable "relationship with the patient" was normalized using One-Hot Encoding. This variable had values such as "child," "sister," "brother," "spouse," and "other." For each value, separate binary integers of 0 and 1 were assigned. Some variables were represented as ratios.

Four ML methods were used on the preprocessed dataset. The initial measurement obtained by utilizing the RF approach to optimize the prediction model's matrix. The RF is a ML technique that creates several DTs during the training process.[28]

The output class is determined by the average prediction of all individual DTs. The RF addresses the issue of overfitting encountered in traditional decision-tree approaches by creating several DTs throughout the training process. Logistic regression is a commonly used method by researchers. This ML technique employs a logistic function to handle two variables that are dependent on class.[29] A DT is constructed by splitting the dataset into branches based on multiple conditions, making it applicable in various fields.[30] SVM, a popular ML technique, aims to identify a support vector by accurately separating the provided training data in a feature space created using a kernel function.[31,32] The ML techniques were implemented using the Python programming language and the Scikit-learn library within the Anaconda environment. To configure the RF algorithm, the "ntree" option was set to 100, specifying the desired number of trees to be created. Increasing the value of "ntree" did not lead to any noticeable improvement. The default parameter values were used for logistic regression and support vector machines (SVM). The SVM employed three well-established kernel functions: linear, polynomial, and sigmoid. A total of six models were implemented using this configuration.

To assess the accuracy of each prediction model, the technique of tenfold cross-validation was utilized. This involved partitioning the dataset into ten equal portions. The models underwent training on nine segments and were subsequently tested on the remaining segments. This process was repeated until all segments were used for testing. A confusion matrix is constructed to assess the performance of each model, using six parameters: accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and ROC curve. Accuracy was given the highest priority, as the primary objective of the study was to identify a prediction model that could effectively predict the variables.[31]

Ethical considerations

Approval for this study was obtained from Mashhad University of Medical Sciences (IR.MUMS.NURSE.REC.1400.006). Strict measures were taken to ensure the confidentiality of participants' information.

Results

In this study, 200 caregivers participated with a mean (SD) age of 42.54 (12.90) years, of whom 55% were female. The mean (SD) number of care days was 5.14 (2.00), the mean (SD) number of dialysis days was 2.97 (1.24), and the mean (SD) number of care hours per day was 10.47 (7.98). Table 3 presents an overview of the descriptive statistics pertaining to caregivers.

The ML techniques were implemented using the Python programming language and the Scikit-learn package in the Anaconda environment. In the RF model, the "ntree" parameter was set to 100, representing the total number of trees generated. Increasing the "ntree" value did not result in any noticeable improvement. The logistic regression, SVM, and DT models were trained using their default parameter values. The SVM algorithm typically utilizes three well-established kernel functions: linear, polynomial, and sigmoid. There were six variations created using this concept. The accuracy and training time were assessed for various values of the ntree parameter (10, 50, 500, and 1000) using 8 features, with the aim of optimizing performance. The analysis is depicted in Figure 3. The average duration of training for eight features was 0.03 seconds when using 10 ntree, and 0.13 seconds while using 100 ntree. The average training duration showed a substantial increase, going from 0.13 seconds for 100 ntree to 0.81 seconds for 500 ntree, and further rising to 1.55 seconds for 1000 ntree. Thus, it can be inferred that the ntree number of 100 resulted in the maximum level of accuracy for parameters that required minimal training time.

Table 4 shows performance and Figure 4 shows the corresponding AUC: the RF model had the greatest

Table 3: Characteristics of Caregivers (*n*=200)

Variable		*n* (%)
Gender	Female	110 (55.00)
	Male	90 (45.00)
Marital status	Married	143 (71.50)
	Single	46 (23.00)
	Divorce	11 (5.50)
Education	Primary school	38 (19.00)
	Secondary school	34 (17.00)
	Diploma	80 (40.00)
	University	48 (24.00)
Job	Housewife	67 (33.50)
	Worker	39 (19.50)
	Employee	38 (19.00)
	Retired	21 (10.50)
	Other	35 (17.50)
Habitat	Urban	144 (72.00)
	Rural	56 (28.00)
Economic situation	Enough	103 (51.50)
	Less than enough	82 (41.00)
	More than enough	15 (7.50)
Relationship with the patient	Child	78 (39.00)
	Spouse	57 (28.50)
	Sister	27 (13.50)
	Brother	22 (11.00)
	Other	16 (8.00)
Help/Care assistance	Not at all	25 (12.50)
	Low	74 (37.00)
	Moderate	48 (24.00)
	High	53 (26.50)
Psychological well-being	Equal or less than mean	111 (55.50)
	More than mean	89 (44.50)
Variable		**Mean (Standard Deviation)**
Age		42.54 (12.90)
Number of family members		5 (2.00)
Number of care days		5.14 (2.00)
Number of dialysis days		2.97 (1.24)
Number of care hours per day		10.47 (7.98)
CBI		62.73 (17.09)
Time dependence burden		14.53 (4.77)
Developmental burden		13.17 (4.50)
Physical burden		10.72 (3.70)
Social burden		10.98 (4.44)
Emotional burden		13.34 (4.28)
Psychological well-being		65.79 (9.92)
Autonomy		11 (1.93)
Environmental Mastery		10.2 (1.72)
Positive Relation		11.58 (2.36)
Personal Growth		11.33 (2.53)
Purpose Life		10.68 (2.43)
Self-Acceptance		11 (2.69)

accuracy (0.72). After the SVM polynomial model (0.68), the SVM sigmoid (0.65), the Logistic Regression (0.61), and SVM linear (0.59), and DT (0.54) models had decreasing orders of performance. The reason for the reduced ROC shown in Figure 4f is that DT uses a combination of multiple DTs to categorize them, so the overall accuracy rate can be very poor because some DTs are often overfitted. Figure 4 depicts the comparison of the accuracy of the ML algorithms: logistic regression, RF, DT, and SVM (linear, polynomial, sigmoid). Figure 5 shows that using many features does not improve performance. The best accuracy achieved by the RF model was 0.70, with eight variables identified as predictors of well-being: caregiver burden, age, number of care days, number of family members, number of dialysis days, education, economic situation, and the amount of assistance provided by family members to the caregiver in relation to caregiving tasks (helper). The best accuracy of the SVM polynomial model was 0.68 and included three variables as predictors of well-being, including Care burden, age, and number of care days. The best accuracy of the SVM linear model was 0.62 and included five variables as predictors of well-being, including education, economic situation, female, urban, and married. The best accuracy of the logistic regression model was 0.58 and included six variables as predictors of well-being, including number of dialysis days, education, economic situation, helper, female, and urban. The best accuracy of the DT model was 0.58 and included four variables as predictors of well-being, including care burden, age, number of family members, and education. The best accuracy of the SVM sigmoid model was 0.54 and included five variables as predictors of well-being, including care burden, age, number of care days, number of care hours per day, and number of family members.

RF identified eight predictors. Logistic regression identified six predictors, SVM linear and SVM sigmoid identified only five predictors, whereas DT and SVM polynomial respectively identified 4 and 3 predictors. The most influential variables for prediction were care burden and age, which were supported by all models except for logistic regression. The education was supported by logistic regression, RF, SVM linear, and sigmoid. The economic situation was supported by logistics regression, RF, and SVM linear. Number of care days was supported by RF, SVM polynominal, and sigmoid. Number of family members was supported by RF, SVM sigmoid, and DT.

Discussion

RF had higher accuracy than alternative methods like polynomial/linear/sigmoid SVM, logistic regression, and DT in this investigation. In the current experiment, the RF algorithm exhibited the highest levels of accuracy (0.70), sensitivity (0.72), and negative predictive value (0.76). Moreover, it demonstrated the highest level of the AUC (0.72). This indicates that the RF algorithm demonstrates a high degree of competence in predicting the well-being of caregivers of persons afflicted with CKD. A prior investigation demonstrated that the RF method

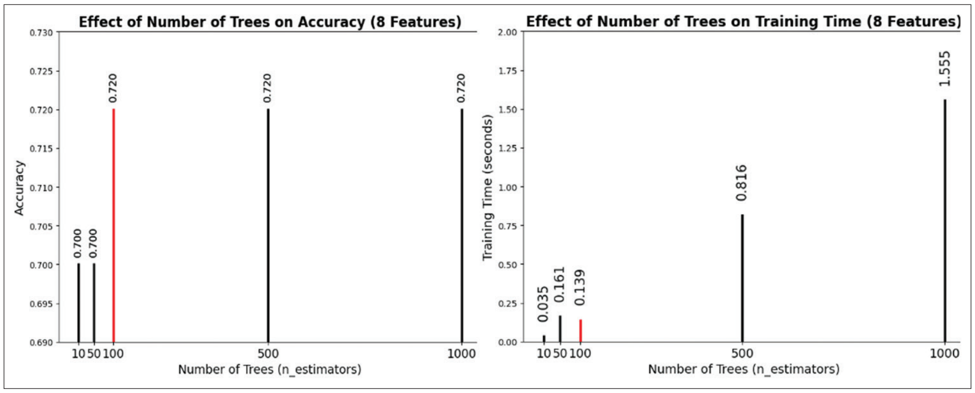

Figure 3: Predicting Modeling by default parameter value

Table 4: Comparison of Performance in Prediction Models

Algorithms	Accuracy	Sensitivity	Specificity	PPV**	NPV***	AUC****
Logistic Regression	0.58	0.50	0.64	0.52	0.62	0.61
Random forest	0.70	0.72	0.67	0.64	0.76	0.72
SVM* linear	0.62	0.5	0.71	0.57	0.64	0.59
SVM polynomial	0.68	0.54	0.78	0.66	0.68	0.68
SVM sigmoid	0.54	0.09	0.89	0.04	0.55	0.65
Decision Tree	0.58	0.50	0.64	0.52	0.62	0.54

*Support Vector Machine (SVM). **Positive Predictive Value (PPV). ***Negative Predictive Value (NPV). ****Area Under the Curve (AUC)

exhibited higher accuracy than alternative algorithms, such as SVM (polynomial/linear/sigmoid) and logistic regression.[33] Among all models, the RF model exhibits the highest Negative Predictive Value (NPV) of 0.76. Consequently, this model has exhibited significantly higher accuracy in forecasting negative cases than other models. Put simply, if the RF model predicts that a caregiver's health state is unfavorable, it is highly probable that this forecast is accurate. The RF model exhibits the highest sensitivity (0.72) compared to all other models, indicating its strong ability to accurately identify caregivers in a suboptimal state of health. Put simply, if a caregiver's health status is poor, the RF model has a 72% chance of accurately detecting it. The model also has a positive predictive value (PPV) of 0.64, meaning that 64% of the positive predictions made by the model are accurate. Alternative models, such as the SVM polynomial, exhibit a PPV of 0.66, whereas the SVM linear has a PPV of 0.57. While the SVM polynomial model exhibits a marginally greater PPV in comparison to the RF model, it is important to take into account the overall balance across metrics. The RF model provides superior equilibrium among various parameters such as accuracy, sensitivity, specificity, positive PPV, NPV, and AUC, rendering it a more favorable option. The RF method is considered the ideal choice since it effectively achieves a favorable equilibrium between accuracy, sensitivity, and specificity. By employing an ensemble of DTs, this approach effectively mitigates the impact of noise and data instability, resulting in enhanced prediction accuracy. Furthermore, this model has consistently sustained its performance even when the number of input variables has been increased, and it has demonstrated the highest level of accuracy when dealing with a greater number of variables. The RF model achieved the highest accuracy rate of 0.70. It utilized eight variables as predictors of well-being, which are: care burden, age, number of care days, number of family members, number of dialysis days, education, economic situation, and the quantity of assistance provided by family members to the caregiver in relation to caregiving tasks (helper). The most influential variables for prediction were care burden and age, which were supported by all models except for logistic regression. Several studies have indicated that caregivers of CKD patients experience a higher level of care burden and a decline in their psychosocial well-being compared to a control group. The psychological demands of CKD patients and their caregivers might adversely affect their health and well-being.[34] Several studies have indicated that older caregivers face more challenges in managing their responsibilities and feel higher levels of stress and worse levels of overall well-being compared to younger caregivers.[35,36] As caregivers age, they experience concerns regarding the future care of their ailing family member. Furthermore, elderly caregivers are unable to deliver optimal care for the ailing individual. The role of gender has often been examined as a determinant of the level of care burden and well-being experienced by caregivers. Various studies have consistently shown that female caregivers experience greater amounts of caregiving responsibility and lower levels of well-being in comparison to their male counterparts.[36-38] However, two studies indicated that this correlation did not achieve a statistically significant

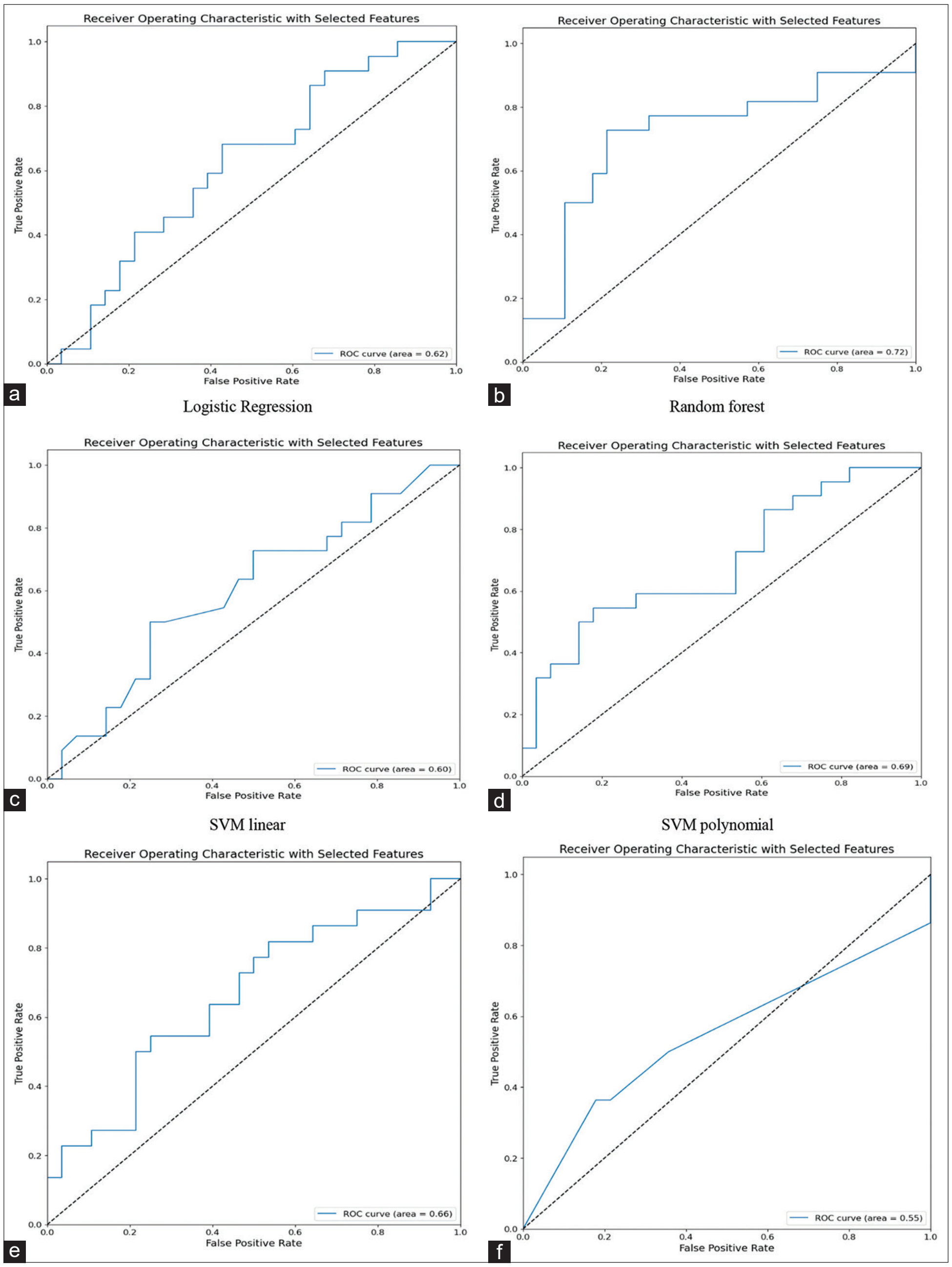

Figure 4: Area under the curve of prediction models. a: Logistic Regression Model, b: Random forest Model, c: SVM linear Model, d: SVM polynomial Model, e: SVM sigmoid Model, f: Decision Tree Model

threshold.[35,39] The education was supported by logistic regression, RF, SVM linear, and sigmoid. A study found that caregivers with higher educational attainment experienced a greater care burden and a lower sense of well-being. Nevertheless, this study found that caregivers who acquire a more advanced level of education in providing support to care recipients feel a reduction in the overall care burden of caregiving.[40] Similarly, caregivers who had sufficient health literacy reported reduced levels of care burden and increased well-being.[41] The economic situation was supported by the implementation of logistic regression, RF, and SVM linear. Several research has investigated the relationship between caregiver income and the level of care burden and well-being. There is a correlation between reduced income of caregivers and increased burden and decreased well-being.[42,43] The number of care days was predicted using RF, SVM (polynomial kernel, and sigmoid). The frequency of dialysis sessions and the presence of comorbidities directly correlate with the increased requirement for care days per week. Expanding the duration of caregiving might heighten the load of caregiving and diminish the overall well-being of the caregiver.[44] Number of family members was supported by RF, SVM sigmoid, and DT. A decrease in the number of individuals assisting the caregiver in providing care results

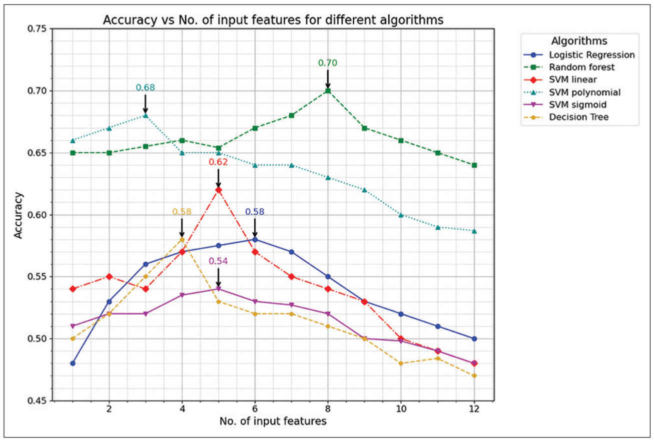

Figure 5: Kernel function of support vector machine

in a decline in the caregiver's psychological well-being. Furthermore, caregivers who actively seek social support from their family and friends tend to report a reduced level of care burden compared to caregivers who lack strong support networks.[38] Classical statistical methods often produce similar results; however, ML is specifically designed to examine raw datasets without the need for particular interpretation or refinement of the data. ML can identify and report on associated characteristics that were not typically documented in prior studies. This study utilized many ML techniques to determine the most suitable strategy. The most significant limitation faced by the authors was related to data quality, as the data were collected through self-reported questionnaires. To ensure the accuracy of the data, follow-up contact was made with participants in some cases.

Conclusion

This study utilized six ML algorithms to forecast parameters associated with the well-being of caregivers of patients with CKD. The RF model obtained the greatest accuracy score of 0.70, followed by the SVM polynomial with a score of 0.68, the SVM linear with a score of 0.62, the logistic regression model, the DT with a score of 0.58, and the SVM sigmoid with a score of 0.54. The RF algorithm proved highly effective in identifying factors that influence the well-being of caregivers of patients with CKD. The RF algorithm attained superior levels of AUC (0.72) and sensitivity (0.72%). Through the use of ML techniques, we have discovered several factors that are associated with the well-being of caregivers of CKD patients. These factors include the level of care burden, the caregiver's age, education level, economic situation, number of care days, number of family members, number of dialysis days, and the amount of assistance provided by family members to the caregiver in relation to caregiving tasks.

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Conflicts of interest

Nothing to declare.

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