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Article

Predicting Nurse Turnover for Highly Imbalanced Data Using SMOTE and Machine Learning Algorithms

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Abstract: Predicting nurse turnover is a growing challenge within the healthcare sector, profoundly impacting healthcare quality and the nursing profession. This study employs the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance issues in the 2018 National Sample Survey of Registered Nurses (NSSRN) dataset and predict nurse turnover using machine learning (ML) algorithms. Four ML algorithms, namely logistic regression (LR), random forests (RF), decision tree (DT), and extreme gradient boosting (XGBoost), are applied to the SMOTE-enhanced dataset. The data is randomly split into an 80% training set and a 20% validation set. Eighteen carefully selected variables from the NSSRN database serve as predictive features, and the machine learning model identifies feature importance concerning nurse turnover. The study includes a performance comparison based on metrics such as Accuracy, Precision, Recall (Sensitivity), F1-score, and AUC. In summary, the results demonstrate that SMOTE-enhanced random forests (SMOTE_RT) exhibit the most robust predictive power, both in the classical approach (with all 18 predictive variables) and an optimized approach (utilizing eight key predictive variables). XGBoost, decision tree, and logistic regression follow in performance. Notably, age emerges as the most influential factor in nurse turnover, with working hours, EHR/EMR usability, individual income, and region also playing significant roles. This research offers valuable insights for healthcare researchers and stakeholders, aiding in selecting suitable ML algorithms for nurse turnover prediction.

Keywords: nurse turnover; machine learning; SMOTE; NSSRN; random forest; XGoost

1. Introduction

The healthcare sector in the United States has undergone a remarkable transformation over the past few decades. Not only has it expanded significantly, but it has also become a driving force behind the nation's economic growth, employing approximately 14.3 million individuals. With projections indicating the creation of an additional 3.2 million healthcare-related jobs soon [1], the healthcare industry's significance in the American economy is set to soar even higher. Beyond its economic impact, healthcare is pivotal in American citizens' lives, as it is fundamentally dedicated to supporting their health and well-being. In recent years, healthcare competition has greatly increased, especially due to the COVID-19 pandemic [2]. Despite the sector's overall commendable performance, significant challenges persist.

One of the most pressing issues plaguing the US healthcare system is the problem of high employee turnover, particularly among nurses. This turnover not only impacts the healthcare

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industry's ability to deliver quality care but also hampers its overall performance. Many nurses leave their current organizations in pursuit of opportunities to enhance their skills and competencies [3]. This phenomenon, called turnover intention, measures how much employees think about leaving their current organization. This significantly affects the organization's sustainability and reputation [4]. Turnover intention represents a process wherein employees contemplate leaving their current organization for various reasons, reflecting their anticipation of voluntarily departing soon [2]. It underscores an employee's contemplation and inclination toward seeking alternative employment. In the healthcare industry, nurse turnover intention has emerged as a pervasive problem, transcending organizational size, location, and nature of business [4]. The adverse impact of high turnover intention on healthcare organizations is keenly felt, as it directly affects the quality of service they can provide [5]. Consequently, extensive research efforts have been dedicated to understanding and evaluating nurse turnover, specifically identifying predictive factors for nurse turnover intention [3], [6]. International studies consistently report a significant increase in nurses expressing their intention to leave their jobs [7], [8]. Hence, the ability to predict nurse turnover has become a crucial procedure for healthcare organizations. Early access to information regarding nurse turnover status empowers organizations to take preemptive measures and implement interventions to curtail turnover, ultimately ensuring the continued delivery of high-quality healthcare services [9].

In this regard, Artificial Intelligence (AI) offers a unique ability to analyze diverse datasets, from structured human resource records to unstructured sources like social media sentiment and employee feedback [10]. This holistic approach provides valuable insights into the factors contributing to turnover. Such factors include work-related stress, job dissatisfaction, or personal circumstances [11]. Human resource departments can identify early warning signs such as increased absenteeism or declining performance of employees [12]. Thus, the healthcare industry can proactively intervene in the turnover intention based on predictive factors. These interventions may include tailored training programs, workload adjustments, or personalized support to address employee concerns [13].

One of the main branches of AI is machine learning (ML) algorithms, which can learn and adapt knowledge based on data training and learn from recurring patterns from the dataset. Then, observed data patterns are used to predict an outcome. Various machine learning algorithms are popular to predict the outcomes in the recent healthcare-related study [14]–[16], which included but not limited to neural networks, extreme gradient boosting, random forest (RF), decision tree, logistic regression, support vector machine (SVM) [7], [9], [13]. In ML, classification algorithms consider that every class should have an approximately equal number, but, in practice, it may fail due to class imbalances [17]. In an imbalanced dataset, we have the class with fewer examples, a so-called minority class, and the class with many examples, a so-called majority class. If an imbalanced dataset is used when performing ML analysis, the imbalanced distribution of the classes may be overlooked. This results in poor performance for the minority class, creating a model bias for the majority class because ML tends to learn more about the majority class during the data partitioning process [18].

The academic significance of our present research lies in the scarcity of open literature studies focused on nurse turnover prediction using machine learning algorithms. While numerous papers have examined the association between various factors and nurse turnover, only a few have delved into the predictive potential of machine learning in this context. Demographic factors such as age, sex, marital status, work experience, and job position have commonly been identified as contributing factors to nurse turnover [19]. Organizational factors, including department, employment status (regular or non-regular), and lower nursing grade, have also been found to predict turnover [20]. Furthermore, research from South Korea highlights additional critical factors such as marriage, childbirth, and child-rearing as significant contributors to nurse turnover [7], [20]–[22]. However, it is essential to note that the most recent study conducted by Bae (2023) employed the 2018 National Sample Survey of Registered Nurses (NSSRN) dataset and utilized multivariable logistic regression for analysis. One notable challenge encountered in the study was dealing with imbalanced data in the context of turnover classification. This challenge serves as a key motivation for our research.

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Previous literature reviews demonstrated that existing approaches have effectively predicted nurse turnover across various datasets. However, diverse machine learning algorithms have been employed without considering class imbalance issues to enhance various performance metrics, including accuracy, precision, and recall. In this study, our primary objective is to compare machine learning techniques alongside the Synthetic Minority Over-sampling Technique (SMOTE) to determine the most effective method for predicting nurse turnover. To our knowledge, this is the first endeavor to comprehensively analyze all dataset features within the NSSRN context.

This study aimed to develop and evaluate a predictive model for nurse turnover in the USA using machine learning. The remainder of this research paper is as follows. Section 2 presents a methodology such as data preprocessing, the ML algorithm, and the SMOTE method. Section 3 presents the experimental results of the study and compares them with existing methods. Section 4 presents the study's conclusion and future research.

2. Method

2.1. Research Framework for Nurse Turnover Prediction Model

First and foremost, data preprocessing was carried out. This phase involved handling missing values and creating dummy variables for categorical data. Once the data preprocessing was complete, the next phase involved the application of the SMOTE method. The objective was to rectify class imbalance in nurse turnover samples between the training (80%) and validation (20%) datasets. This step aimed to enhance the accuracy of the machine learning models used for nurse turnover prediction by increasing the sample size. SMOTE, an oversampling technique, was chosen for this task due to its effectiveness in addressing the issue of highly imbalanced data, a common challenge in machine learning studies. Following resolving the data imbalance, the subsequent phase entailed the development of machine learning algorithms for training and predicting nurse turnover. Four distinct models were employed for this purpose: Logistic Regression (LR), Random Forest (RF), Decision Tree (DT), and Extreme Gradient Boosting (XGBOOST). A grid search was used to select the best parameters for each model to optimize the performance of these models. Afterward, the performance of these models was assessed using five key performance metrics: accuracy, recall (sensitivity), precision, F1-Score, and area under the curve (AUC). The overall framework of the proposed intelligent approach for predicting nurse turnover is visually represented in Figure 1.

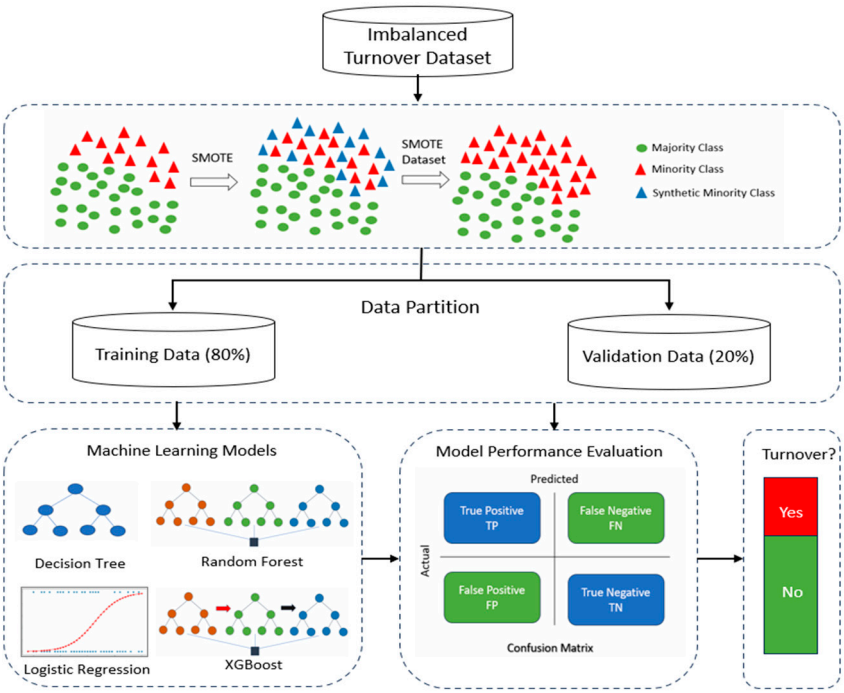

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Figure 1. Overall Framework of Nurse Turnover Prediction.

2.2. Data Collection and Data Preprocessing

We conducted a study using the publicly available 2018 National Sample Survey of Registered Nurses (NSSRN) to estimate nurse turnover rates in the United States, as reported by HRSA in 2023 [23]. The NSSRN is designed to capture various characteristics of nurses, including demographics, employment details, and licensing and certification status. Data were collected from April to October 2018, with 102,520 registered nurses (RNs) invited to participate. A total of 50,273 nurses completed the survey, resulting in an unweighted response rate of 50.1% and a weighted response rate of 49.1%.

Our study focused on RNs, Nurse Practitioners (NPs), Clinical Nurse Specialists (CNSs), Nurse Anesthetists (NAs), and Nurse-Midwives (NMs) who were working as of December 31, 2017. After excluding records with missing values, our dataset included 43,987 samples. Among these records, 89% indicated turnover ("Yes"), while 11% indicated no turnover ("No"), indicating an imbalanced dataset.

For our analysis, we selected 18 relevant variables from the NSSRN database based on prior literature [2], [6], [7]. These variables are listed in Table 1, and we renamed them from the NSSRN codebook for clarity. We converted categorical variables into factor levels to facilitate machine learning analysis, as ML algorithms require numerical inputs [10]. Subsequently, we randomly split the dataset into an 80% training set and a 20% validation set.

Table 1. Description of feature used for ML analysis.

Feature Name	Data Type	Description
Turnover (Dependent Variable)	Categorical	Outcome feature: showing whether the nurse left the primary nursing position (1: Yes, 0: No)
Certificate	Categorical	Type of active certification (three-factor levels) NP: Nurse Practitioner, RN: Registered Nurse, Other: Combined variable(Clinical Nurse, Nurse Midwife, Nurse Anesthetist)
Region	Categorical	Location of primary nursing position-census division (four-factor levels: West, Midwest, South, and North)
Job_Satisfaction	Categorical	Levels of job satisfaction in primary nursing position (Satisfied vs. Dissatisfied)
Race	Categorical	Race (White vs. other race (Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander, Some other race))
Sex	Categorical	Sex (Male vs. Female)
Marital_Status	Categorical	Marital Status (Single vs. Married); widow, divorced, and separated is considered as Single
Veteran	Categorical	Veteran Status (Served vs. Never served); active duty for training and now or past active duty is considered as Served
Household_Income	Categorical	Pre-tax annual household income (three-factor levels): $75,000 or less, between $75,000 and $15,000, and More than $150,000
Degree	Categorical	Type of nursing degree: three-factor levels (AND: associate degree, BSN: Bachelor's degree, MSN: Master's degree, PhD/DNP/DN: Doctorate)
Dependent_6years	Categorical	A binary value indicating whether the nurse lives at home with a dependent who is less than 6 years old (Yes vs. No)
EHR_EMR	Categorical	Usability of Electronic Health Record (HER) or Electronic Medical Record (EMR) system (Yes vs. No)

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Employment_Type	Categorical	Primary nursing position employment situation (Employed by the organization vs. other (employment agency as a traveling nurse, not as a travel nurse, and self-employed or working as needed))
Job_Type	Categorical	Full-time vs. Part-time work
Employment_Setting	Categorical	Type of work setting (three-factor levels: Hospital, Clinic/Ambulatory, and Inpatient + other work setting)
Practice	Categorical	Ability to practice to the extent of knowledge/education/training (Yes vs. No)
Working_Hour	Categorical	Number of hours worked in a typical week (Standard vs. Overtime); working hours greater than 40 is regarded as overtime
Individual_Income	Numerical	Pre-tax annual earnings from primary nursing position ($)
Age	Numerical	Age of nurse

2.3. Sampling Method

After establishing training and validation datasets, we employed the Synthetic Minority Over-sampling Technique (SMOTE) to rectify the class imbalance issue within the new training dataset. This approach substantially improved the distribution of each class, mitigating any potential bias towards the minority class [24]. SMOTE accomplished this by augmenting the quantity of data instances by generating synthetic data points for the minority class derived from its nearest neighbors based on the Euclidean distance metric [25]. As a result, the newly generated instances exhibited a heightened resemblance to the original data distribution [26]. Before applying SMOTE, the class distribution for nurse turnover displayed a majority-minority split of 89% and 11%, respectively. However, following the implementation of the SMOTE method, these proportions shifted to 57% and 43%. A visual representation of the SMOTE's impact on our turnover dataset can be observed in Figure 2.

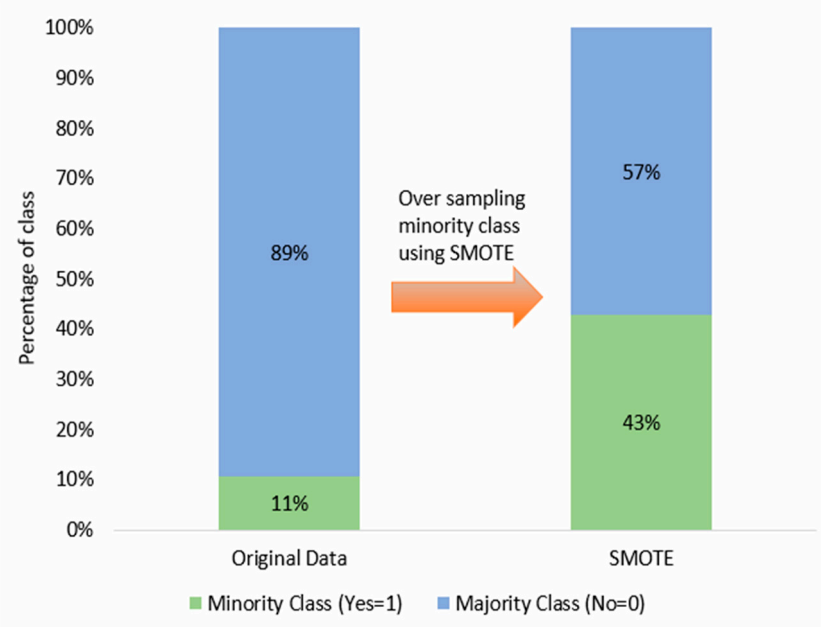

Figure 2. Illustration of SMOTE Process for Turnover Data.

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2.4. Machine Learning Models

2.4.1. Decision Tree (DT)

Decision Tree (DT) is a non-parametric supervised learning algorithm for prediction and classification [27]. A decision tree is a tree-like structure containing internal, branch, and leaf nodes. Each internal node represents a judgment on an attribute, each branch represents the output of a judgment, and each leaf node represents a prediction or classification result. A decision tree is a root-to-leaf recursive process that includes feature selection, decision tree construction, and pruning.

Feature selection is selecting an appropriate attribute to partition the sample at each node. It is important as it can decide the decision tree's breadth and depth. The goal is to make the classified dataset relatively pure, which means records resembling each other in each classified portion. The Gini index or Entropy measure can measure a dataset's impurity. The Gini index is mainly used in the Classification and Regression Tree (CART) decision tree algorithm as a classification standard. In this study, we use CART as a predictive algorithm, which is good at handling both continuous and discrete variables.

The formula of the Gini index for dataset A is shown in equation (1). In the equation, k is one class of the dependent variable, and p_k is the proportion of records in a classified portion that belong to class k. Obviously, the smaller the number of $Gini(A)$, the higher the purity of dataset A.

$$Gini(A) = 1 - \sum_{k=1}^{m} p_k^2 \qquad (1)$$

When dataset A is binary split on a certain value x based on attribute X into two subsets A_1 and A_2, the Gini index for the split dataset A is shown in equation (2). For a specific attribute X, calculate the corresponding Gini index for each value x separately and select the smallest value as the optimal binary scheme obtained by attribute X.

$$Gini_{X=x}(A) = \frac{|A_1|}{A} Gini(A_1) + \frac{|A_2|}{A} Gini(A_2) \qquad (2)$$

Then, repeat the process for all the attributes, obtain all the optimal binary schemes, and select the smallest of them as the dataset's optimal segmentation attribute.

Decision tree construction depends on the feature selection process. The whole dataset A is the root node. After obtaining the optimal attribute and value that yields the purest dataset, the resulting split points become nodes on the decision tree. This recursive partitioning process continues until a full-grown tree is constructed.

The final process is pruning the full-grown tree to avoid overfitting. Overfitting is a phenomenon in which the error rate of the training sample decreases to 0. Still, the error rate of the validation or test sample is pretty high as it has a first downward and then upward trend with the number of splits. The key to pruning is to find the point at which the error rate of the validation sample is at a minimum. The CART algorithm uses a validation dataset to prune back the full-grown tree generated by the training dataset. It uses a cost complexity pruning strategy that designs an indicator to measure the complexity cost of a subtree and prunes by setting a threshold at this cost. The greater the cost, the greater the deviation caused by pruning; that is, the less it can be pruned.

2.4.2. Random Forest (RF)

Random Forest (RF) is a multi-tree ensemble learning approach that applies the concept of Bagging to improve the weak generalization ability of a single decision tree [32]. Bagging, or bootstrap aggregating, is an algorithm that randomly selects several subsets as training data, uses them to construct several models, and then takes the average or majority vote as the output results. RF is a stable and effective classifier that integrates many decision trees. The process of constructing a single decision tree is represented in the previous section. The training data used to construct a tree is generated by random sampling with replacement from the whole dataset, assuming 80% of the total records in this study.

Then, with numerous different training datasets, we construct many decision trees that form a random forest as a whole. Choosing the optimal number of decision trees in an RF is important as it relates to the correlation and classification ability of any two trees in the RF. This parameter can be decided by calculating and comparing the out-of-bag error for different RF models. The smaller the

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out-of-bag error is, the better the RF model is. The out-of-bag error is the ratio of misclassified records to the total number of records.

The class decides the classification or prediction of the final RF model with the majority vote of decision trees. For example, if there is an RF model that consists of 100 decision trees, we find that the voting result of 70 trees is 1 for a specific record and the voting result of the other 30 trees is 0, then the final classification is 1 for this record. RF is good at handling high-dimensional data as well as imbalanced datasets at a fast speed. In addition, it can provide relative importance for different variables for decision-makers.

2.4.3. Logistic Regression (LR)

Logistic Regression (LR) is a generalized linear regression analysis model mainly used for binary classification [29]. For binary LR, the dependent variable only has two classes denoted as 1 and 0, and the independent variables can be numerical and categorical. Assuming that under the impact of the independent variables $(x_1, x_2, \dots, x_q)$, the probability of the dependent variable (y) being "1" is p, and the probability of being "0" is $1-p$. Then, the goal of LR is to investigate the relationship between the probability p and the independent variables, shown in equation (3). Odds denote the ratio of probabilities of the dependent variable (y) being "1" and being "0," as shown in equation (4). By combining equations (3) and (4), we obtain equation (5).

$$p = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_q x_q)}} \quad (3)$$

$$Odds = \frac{p}{1-p} \quad (4)$$

$$Odds = e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_q x_q} \quad (5)$$

Finally, taking natural logarithms on both sides of equations (4) and (5), we can obtain the LR model, as shown in equation (6). In equation (6), $ln\left(\frac{p}{1-p}\right)$ is called logit, and it has a linear relationship with independent variables. The coefficients $(\beta_0, \beta_1, \beta_2, \dots, \beta_q)$ in the model is estimated using the Maximum Likelihood Estimate algorithm. The LR model has high computational efficiency and can clearly explain the impact of different independent variables on the dependent variable by checking the odds ratio.

$$ln\left(\frac{p}{1-p}\right) = ln(odds) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_q x_q \quad (6)$$

2.4.4. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is a widely used machine learning algorithm based on a decision tree ensemble [28]. It introduces parallel computing and regularization terms based on the original Gradient Boosting Decision Tree (GBDT) algorithm, thereby improving the model's performance and computational efficiency. XGboost consists of decision trees, which are called "weak learners." But unlike RF, the decision trees that make up XGBoost have a sequential order, and the generation of the latter decision tree is related to the previous decision tree's prediction. XGBoost is an additive model where the model's predicted value is the sum of the predicted values of all individual decision trees.

2.4.5. Performance Metrics

Confusion matrix is used to evaluate the prediction and classification performance of different machine learning algorithms. Confusion matrix is a commonly used metric for classification. It is a situation analysis table that summarizes the records in the dataset in the form of a matrix according to the two criteria of the real category and the predicted category [25]. As shown in Table 2, the matrix columns represent the true values, and the matrix rows represent the predicted values [27].

True Positive (TP): Legitimate records correctly identified as legitimate.
True Negative (TN): Fraudulent records correctly identified as fraudulent.
False Positive (FP): Fraudulent records incorrectly identified as legitimate.
False Negative (FN): Legitimate records incorrectly classified as fraudulent.

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Table 2. Confusion Matrix Index.

Confusion Matrix		True class	
		Positive (Turnorver=Yes)	Negative (Turnorver=No)
Predicted class	Positive (Turnorver=Yes)	TP (True Positive)	FP (False Positive)
	Negative (Turnorver=No)	FN (False Negative)	TN (True Negative)

The confusion matrix provides essential performance metrics, including Accuracy, Recall (Sensitivity), Precision, and the F1-score. These metrics are crucial indicators for evaluating the model's performance [13]. The Area Under the Curve (AUC) score maximizes both recall and specificity, falling within the range of [0,1]. AUC scores between 0.5 and 0.6 are considered inadequate, scores between 0.6 and 0.7 are typical, scores between 0.7 and 0.8 are good, scores between 0.8 and 0.9 are very good, and scores above 0.9 are deemed excellent [28]. We calculate the performance metrics based on the following equations:

$$Accuracy = \frac{(TP + TN)}{(TP + FN + FP + TN)} \quad (7)$$

$$Precision = \frac{(TP)}{(TP + FP)} \quad (8)$$

$$Recall(Sensitivity) = \frac{(TP)}{(TP + FN)} \quad (9)$$

$$F1\text{–}Score = \frac{(2 * (Precision * Recall))}{(Precision + Recall)} \quad (10)$$

3. Results

3.1. Experiment Setup

All data processing, sampling, and machine learning analyses were conducted using the R statistical software, a freely available open-source tool.

3.2. Characteristics of the Participants

The characteristics of 43,937 nurses are summarized in Table 2. A total of 4,728 nurses (11%) left their primary nursing positions. Among the turnover group, those holding NP and RN qualifications tended to leave their positions, accounting for 45.96% and 44.67%, respectively. Most nurses expressed satisfaction with their primary nursing positions, with 9.77% reporting dissatisfaction and 90.23% reporting satisfaction. On average, the age of the nurses was 55 ± 11 years, individual income averaged $70,856 ± 41,404, and they worked an average of 346 ± 14.4 hours per week. In terms of race, 86.51% of nurses were White, and 91.10% were female among those in the turnover group. Furthermore, 75.04% of those who left their positions were married, and 93.97% of nurses reported no prior military service. Regarding household income, 21.49% of nurses earned less than $75,000, 43.46 of nurses earned between $75,000 and $150,000, and 35.05% are more than $150,001. When it came to their educational backgrounds, more than half (57%) held advanced degrees such as MSN and PhD/DNP/DN. Most nurses (82.38%) did not have dependents under the age of 6, and 90.08% were hired by organizations and working full-time (79.61%). In terms of employment setting, 34.01% of nurses worked in clinical/ambulatory settings, followed by hospitals (43.53%) and inpatient/other types of settings (22.46%). Finally, 78.79% of nurses reported that they could practice to the extent of their knowledge, education, and training.

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Table 2. Distribution of the characteristics of the 18 extracted variables in the NSSRN database.

Characteristic	Turnover		Turnover	
	Yes (N=4728), 11%		No (N=39209), 89%	
Categorical Variables	Count	Percentage	Count	Percentage
Certificate				
Other	443	9.37%	2748	7.01%
NP	2173	45.96%	19382	49.43%
RN	2112	44.67%	17079	43.56%
Region				
Midwest	1059	22.40%	8950	22.83%
North	893	18.89%	7227	18.43%
South	1574	33.29%	13084	33.37%
West	1202	25.42%	9948	25.37%
Job_Satisfaction				
Dissatisfied	462	9.77%	3867	9.86%
Satisfied	4266	90.23%	35342	90.14%
Race				
Other Race	638	13.49%	5686	14.50%
White	4090	86.51%	33523	85.50%
Sex				
Female	4307	91.10%	35847	91.43%
Male	421	8.90%	3362	8.57%
Marital Status				
Married	3548	75.04%	29490	75.21%
Single	1180	24.96%	9719	24.79%
Veteran				
Never Served	4443	93.97%	36919	94.16%
Served	285	6.03%	2290	5.84%
Household_Income				
Less than $75,000	1016	21.49%	8418	21.47%
$75,001 TO $150,000	2055	43.46%	17369	44.30%
More than $150,001	1657	35.05%	13422	34.23%
Degree				
ADN	773	16.35%	5891	15.02%
BSN	956	20.22%	9395	23.96%
MSN	2404	50.85%	20308	51.79%
PHD/DNP/DN	595	12.58%	3615	9.22%
Dependant < 6years				
No	3895	82.38%	32248	82.25%
Yes	833	17.62%	6961	17.75%
EHR_EMR Usability				
No	488	10.32%	4595	11.72%
Yes	4240	89.68%	34614	88.28%
Employment_Type				
Employed by Organization	4448	94.08%	36540	93.19%
Other	280	5.92%	2669	6.81%
Job_Type				
Full Time	3764	79.61%	30964	78.97%
Part Time	964	20.39%	8245	21.03%
Employment_Setting				

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Clinical/Ambulatory	1608	34.01%	13110	33.44%
Hospital	2058	43.53%	17551	44.76%
Inpatient/Other	1062	22.46%	8548	21.80%
Practice				
No	1003	21.21%	8512	21.71%
Yes	3725	78.79%	30697	78.29%
Numerical Variables	Count	Std.dev	Count	Std.dev
Age	55	11	48	12
Individual Income	70,285	41404	85,444	37157
Working Hour (per week)	34	14.4	39	11.2

3.3. Machine Learning Analysis Results

In this study, we conducted a comprehensive analysis of supervised machine learning classifiers after implementing the Synthetic Minority Over-sampling Technique (SMOTE) on our dataset. Our primary goal was to evaluate the predictive accuracy and performance of five distinct machine learning algorithms, namely SMOTE-enhanced Logistic Regression (SMOTE_LR), SMOTE-enhanced Random Forest (SMOTE_RF), SMOTE-enhanced Decision Trees (SMOTE_DT), and SMOTE-enhanced XGBoost (SMOTE_XGB), in the context of predicting nurse turnover.

Table 3 displays the outcomes of the logistic regression (LR) model, presenting odds ratios (ORs), 95% confidence intervals (CIs), and p-values at a 95% significance level, which shed light on the influence of each variable on nurse turnover. Notably, we treated NP as the reference category. Individuals falling under the category of Other (comprising NA and NM) are 1.592 times more likely to experience turnover than those in the NP group, assuming all other variables remain constant (CI: 1.42-1.78). Nurses residing in the South and West regions show a decreased likelihood of turnover (OR=1.037, CI: 0.95-1.14). Additionally, nurses who make use of Electronic Health Records (EHR) or Electronic Medical Records (EMR) technology exhibit a reduced likelihood of turnover (OR=0.567, CI: 0.52-0.62).

When considering Employee by Organization as the reference category, other types of employment (such as Travel Nurses and the self-employed) are associated with a substantial increase in the odds of turnover (OR=2.525, CI: 2.29-2.78). Among different job types, part-time nurses have 1.446 times the odds of turnover compared to their full-time counterparts under constant conditions. Furthermore, nurses working in inpatient or other settings exhibit a moderately increased likelihood of turnover (OR=1.248, CI: 1.15-1.35). Notably, individuals working standard work hours are less likely to experience turnover (OR=0.732, CI: 0.69-0.78). Having fewer opportunities for job practice is associated with an increased likelihood of turnover. Male nurses, single individuals, and veterans are more likely to experience turnover. Concerning race, White individuals are less likely to turnover (OR=0.538, CI: 0.50-0.58). A household income of more than $150,001 significantly increases turnover, as indicated by the model ($p<0.05$). On the other hand, individuals with a BSN (OR=0.726, CI: 0.66-0.80) and MSN (OR=0.730, CI: 0.80) are less likely to turnover. Having dependents under 6 years old is linked to a moderately increased likelihood of turnover (OR = 1.357, CI: 1.25-1.47). Lastly, higher age and nurse income decreased nurse turnover.

Table 3. Predictors of nurse turnover using a SMOTE_LR algorithm.

Independent Variables	Odds Ratio	95% CI	p-Value
Certificate (ref:NP)			
Other	1.592	(1.42,1.78)	***
RN	1.032	(0.96,1.11)	
Region (ref: Midwest)			
North	1.037	(0.95,1.14)	
South	0.837	(0.77,0.91)	***
West	0.873	(0.80,0.95)	**

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EHR/EMR Usability (ref:No)			
Yes	0.567	(0.52,0.62)	***
Employment Type (ref: Employed by Organization)			
Other	2.525	(2.29,2.78)	***
Job Type (ref: Full time)			
Part Time	1.446	(1.34,1.56)	***
Employment Setting (ref: Clinical/Ambulatory)			
Hospital	0.881	(0.82,0.95)	***
Inpatient/Other	1.248	(1.15,1.35)	***
Working Hour (ref: Overtime)			
Standard	0.732	(0.69,0.78)	***
Job Satisfaction (ref: Dissatisfied)			
Satisfied	0.469	(0.43,0.51)	***
Job Practice (ref: No)			
Yes	0.577	(0.54,0.62)	***
Race (ref: Other race)			
White	0.538	(0.50,0.58)	***
Sex (ref: Female)			
Male	2.111	(1.93,2.31)	***
Marital Status (ref: Married)			
Single	1.529	(1.43,1.64)	***
Veteran Status (ref: Never served)			
Served	2.154	(1.94,2.39)	***
Household Income (ref: $75,001 to $150,000)			
$75,000 or less	1.048	(0.96,1.14)	
More than $150,000	1.092	(1.02,1.17)	*
Degree (ref: ADN)			
BSN	0.726	(0.66,0.80)	***
MSN	0.730	(0.66,0.80)	***
PHD/DNP/DN	1.121	(1.00,1.26)	
Dependent less than 6 years old (ref: No)			
Yes	1.357	(1.25,1.47)	***
Individual Income	0.999	(1.00,1.00)	
Age	0.998	(0.99,1.01)	
*** p < 0.05, ** p < 0.01, *** p < 0.001.**			

Figure 3 depicts the default Decision Tree analysis results for nurse turnover. At the root node (node 1), we find all the records from the training dataset, comprising 43% “Yes” and 57% “No” outcomes in our target variable (Turnover). The “0” within the top node’s box signifies the majority of nurses who did not leave their jobs.

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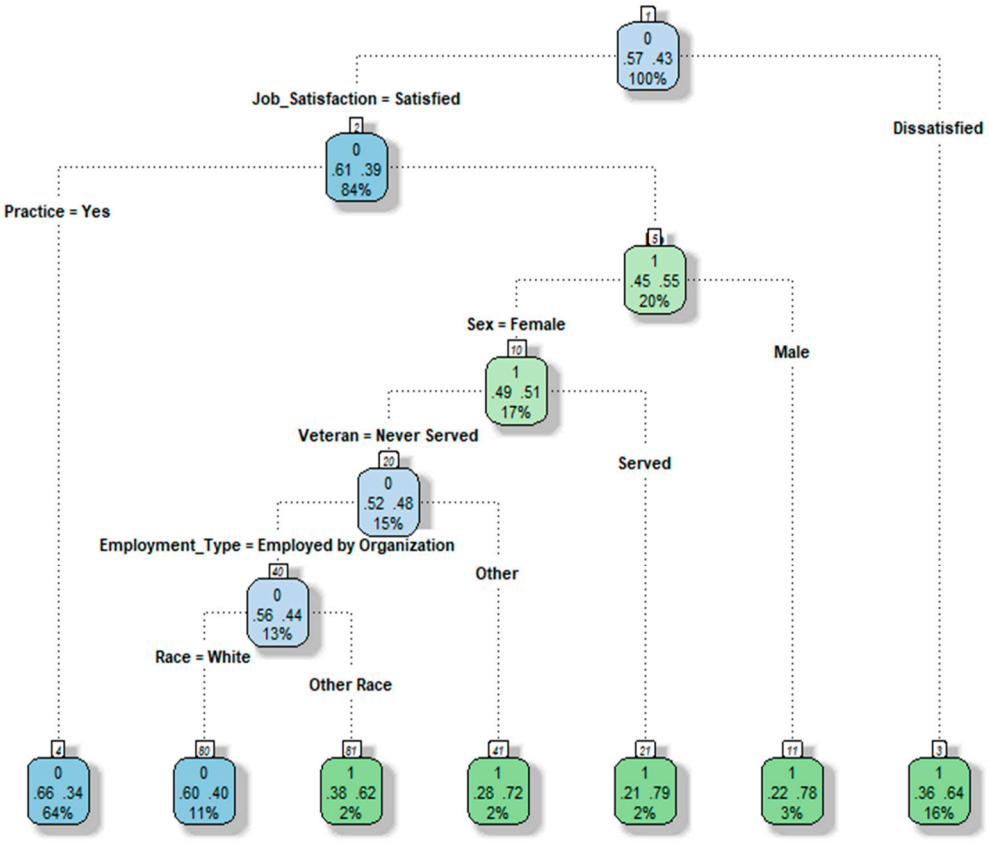

Figure 3. SMOTE_DT Results.

The first node occurs at the Job Satisfaction node (node 2), where 84% of nurses report job satisfaction, with a 39% turnover probability. In contrast, if nurses express dissatisfaction with their jobs (16%), they move to the terminal node (3) with a 64% probability of turnover.

Nurses who are satisfied with their jobs but cannot practice have a 55% chance of turnover (node 5). Notably, male nurses who were unable to practice in their jobs exhibited a higher turnover probability of 78%. Furthermore, nurses serving in the military, working as travel nurses, or in other roles, along with those of non-white ethnicity, show a notably high probability of turnover. The terminal nodes represent the final Decision Tree for nurse turnover. Among the seven terminal nodes, two are associated with the classification "Did not Turnover," while four lead to the "Turnover" classification. The Decision Tree analysis identifies the most influential variables for turnover as Job Satisfaction, followed by Job Practice, Gender, Veteran status, Employee Type, and Race.

3.4. Feature Importance of ML Models

Based on different feature importance criteria, SMOTE_RF, SMOTE_XGB, and SMOTE_DT provide importance rankings for relevant variables in predicting turnover using the mean decrease accuracy score. Figure 4 displays the mean decrease in accuracy and ranking of 18 variables under three different SMOTE-based ML models.

From SMOTE_RF, the top five important variables for predicting turnover were AGE (1), WORKING_HOUR (0.88), HER_EMR (0.67), INDIVIDUAL_INCOME (0.66), and JOB_TYPE (0.62). In the SMOTE_XGB results, WORKING_HOUR (0.42), AGE (0.13), INDIVIDUAL_INCOME (0.09), EHR_EMR (0.08), and JOB_TYPE (0.05) were identified as important features. SMOTE_DT revealed that WORKING_HOUR (1), JOB_TYPE (0.63), INDIVIDUAL_INCOME (0.36), AGE (0.32), and EMPLOYMENT_TYPE (0.02) were the most important features. Blytt et al. (2022) showed an association between working hours and turnover intention. Nurses with higher working hours tend

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to seek jobs with preferable working time arrangements. Age was an important factor in turnover intention. Previous research found that new graduate nurses, who are usually young, have a higher turnover than experienced nurses because they tend to quit their jobs to seek career advancement [21].

Conversely, SMOTE_RF, DEPENDANT_6YEARS (0.31), CERTIFICATE (0.32), DEGREE (0.34), SEX (0.37), and MARITAL (0.39) exhibited the lowest mean decrease scores, indicating that they are the least important variables for predicting nurse turnover. SMOTE_XGB, JOB_SATISFACTION (0), HOUSEHOLD_INCOME (0.01), MARITAL (0.01), DEGREE (0.01), and DEPENDANT_6YEARS (0.01) had the lowest mean decrease scores, making them the least important variables for prediction. SMOTE_DT identified REGION (0), JOB_SATISFACTION (0), MARITAL (0.01), RACE (0.02), and Certificate (0.03) as the least important variables. SMOTE_LR was excluded from the analysis because it provides variable importance for the entire set of predictive variables, preventing us from comparing variable rankings and their correlations. However, we compare SMOTE_LR with other models in terms of performance index.

In terms of correlation analysis, strong positive correlations were observed between SMOTE_DT and SMOTE_XGB (0.86). Moderate-strong correlations were found between SMOTE_RF and SMOTE_XGB (0.68) and between SMOTE_SGB and SMOTE_RF (0.68). Notably, the top five predictors identified in SMOTE_RF, SMOTE_XGB, and SMOTE_DT were also significant in the SMOTE_LR model (see Table 4).

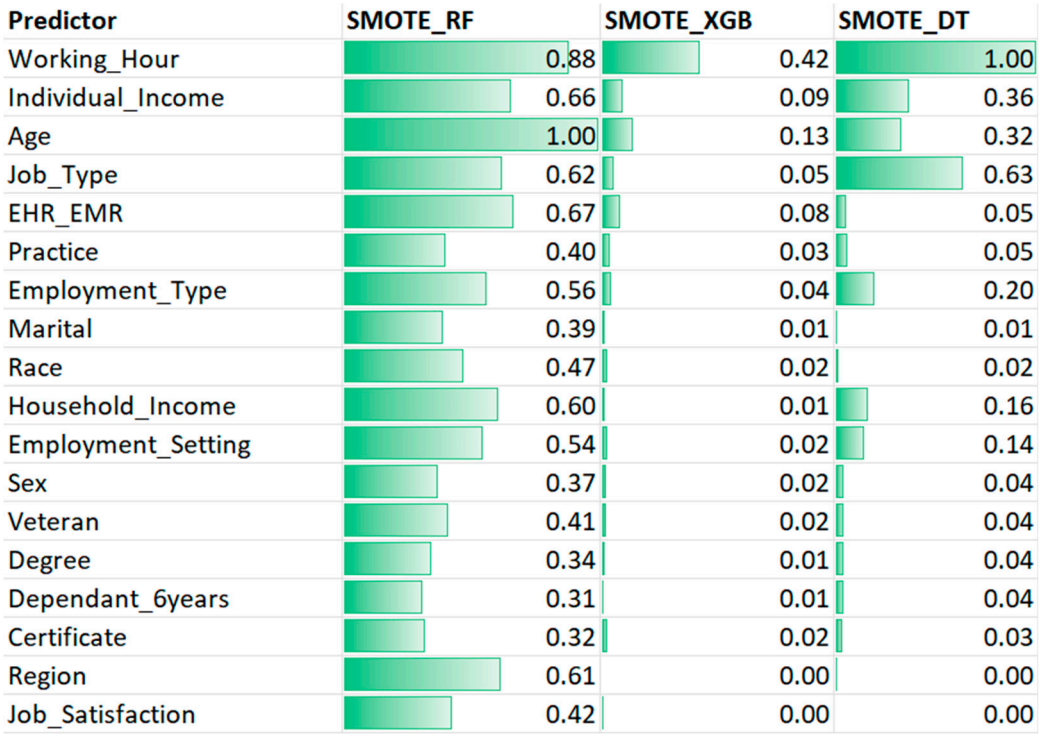

Figure 4. Feature Importance for Predictor Using SMOTE Random Forests, SMOTE_XGB, and SMOTE_DT.

Table 4. Correlation of variable importance for four different models.

	SMOTE_RF	SMOTE_XGB	SMOTE_DT
SMOTE_RF	1		
SMOTE_XGB	0.683893	1	
SMOTE_DT	0.683749	0.861878	1

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3.5. ML Model Performance of Nurse Turnover Prediction

This study evaluated the performance of five different machine learning models using a confusion matrix. Table 5 presents a summary of the classification model indices, including True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The validation dataset consisted of 20% of the total data, with a sample size of 5,295 individuals. In terms of True Positives (TP), SMOTE_RF demonstrated the highest TP rate at 51.3%, correctly predicting the departure of 2,714 out of 5,295 individual nurses from their primary jobs. SMOTE_XGBT followed closely with a TP rate of 51.0%, accurately predicting 2,701 departures. Specifically, SMOTE_RF correctly identified 2,623 instances of nurses leaving their primary jobs, indicating that 51.3% of the cases predicted as job departures corresponded to actual departures.

On the other hand, examining the False Negatives (FN) area, SMOTE_RF exhibited the lowest True Negatives (TN) rate at 5.8%, predicting 312 out of 5,295 cases as job departures when they did indeed leave their primary jobs. This implies that SMOTE_RF incorrectly classified instances as negative cases when they should have been positive. Thus, the model failed to identify only 312 cases that were part of the positive class. Conversely, SMOTE_LR achieved the highest False Positive (FP) rate at 19.6%, correctly predicting 1039 out of 5,295 nurses who did not leave their primary jobs. The model, however, missed 2450 instances that were actually part of the positive class. In terms of the proportion of correct predictions (TP+TN) in the confusion matrix, SMOTE_RF accurately classified 83.6% of the cases, SMOTE_XGBT achieved 82.7% accuracy, while SMOTE_DT and SMOTE_LR achieved 78.3% and 69.5% accuracy, respectively.

Table 5. Confusion matrix of five prediction models.

SMOTE_DT		True class	
		Positive	Negative
Predicted class	Positive	2623(49.5%)	745(14.1%)
	Negative	403(7.6%)	1524(28.8%)
SMOTE_XGB		True class	
		Positive	Negative
Predicted class	Positive	2749(51.0%)	277(6.1%)
	Negative	592(11.2%)	1677(31.7%)
SMOTE_RF		True class	
		Positive	Negative
Predicted class	Positive	2714(51.3%)	561(10.6%)
	Negative	312(5.9%)	1708(32.3%)
SMOTE_LR		True class	
		Positive	Negative
Predicted class	Positive	2450(46.3%)	1039(19.6%)
	Negative	576(10.9%)	1230(23.2%)

Table 6 provides an evaluation of five machine learning methods used in this study, using a set of commonly employed metrics for assessing machine learning algorithms. We have constructed classification metrics, specifically Accuracy, Recall (Sensitivity), Precision, and F1-Score, to compare the performance of our models. Accuracy quantifies the number of correct classifications as a percentage of the total classifications made by a classification model. Precision represents the proportion of positive classifications that are accurately identified, while recall measures the proportion of all positive classifications correctly classified. The F1-Score is a metric that combines precision and recall using their harmonic mean. When considering accuracy, SMOTE_RF and SMOTE_XGB emerge as the optimal models, each achieving similar Accuracy scores of 83.93% and 83.59%, respectively. Conversely, SMOTE_LR (75.90%) and SMOTE_DT (78.30%) exhibited the lowest predictive accuracy. Examining precision, SMOTE_XGB stands out as the best-performing model with a precision score of 89.25%. However, when evaluating the F1-Score, SMOTE-RF emerges

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as the optimal model at 94.02%, particularly when we consider false negatives (FN) and false positives (FP) to be of greater concern.

On the other hand, considering the area under the curve (AUC), the model with the highest AUC score is SMOTE_RF, with an AUC of 82.67%. It's worth noting that AUC is not influenced by the threshold used in the ML classification or the distribution of the dataset. Thus, it provides a comprehensive measure of the classification power of the ML model. Consequently, SMOTE_RF is the preferred choice as the optimal model for predicting nurse turnover. It's interesting to note that our results are similar to the findings of Kim et al. (2023). In their study, RF was identified as the best predictive model.

Table 6. The correct classification metrics for each machine learning method.

CRITERION	SMOTE_LR	SMOTE_RF	SMOTE_DT	SMOTE_XGB
ACCURACY	69.50%	83.93%	78.30%	83.59%
RECALL(SENSITIVITY)	80.96%	89.69%	67.17%	85.82%
PRECISION	70.22%	82.87%	77.88%	89.25%
F1-SCORE	75.08%	94.02%	93.08%	83.90%
AUC	73.59%	82.67%	81.72%	82.38%

3.6. Optimized Random Forest Analysis Result

In this section, we employed an optimized RF analysis to determine the optimal number of features based on their importance. We utilized 18 independent variables and one dependent variable for our model. The process involved running the model 18 times and progressively eliminating lower-scoring features. Our analysis revealed that the accuracy began to decline when only the top eight features in Figure 5 were retained. Consequently, we selected these eight features as the key predictors for the nurse turnover prediction problem. Age, Working Hours, Employment Type, Individual Income, Race, Job Type, Region and HER_EMR were the most important features of the recursive RF analysis. This dimensionality reduction enhances interpretability, especially for handling unbalanced characteristics, as demonstrated by [29]. Reducing the dataset's dimensionality serves a valuable purpose. It equips the human resources department with a more accurate tool for predicting nurse turnover. Rather than concentrating on many predictive variables, the human resources department can achieve more effective interventions in reducing the turnover rate by focusing on a smaller set of variables. Thus, the experimental findings offer valuable insights into reducing nurse turnover intention. In Table 7, we can see that SMOTE_RF shows better performance again for the index for Accuracy, Recall, Precision, F1-score, and AUC than algorithms SMOTE_DT, SMOTE_XGB, and SMOTE_LR, which implies better predictive ability.

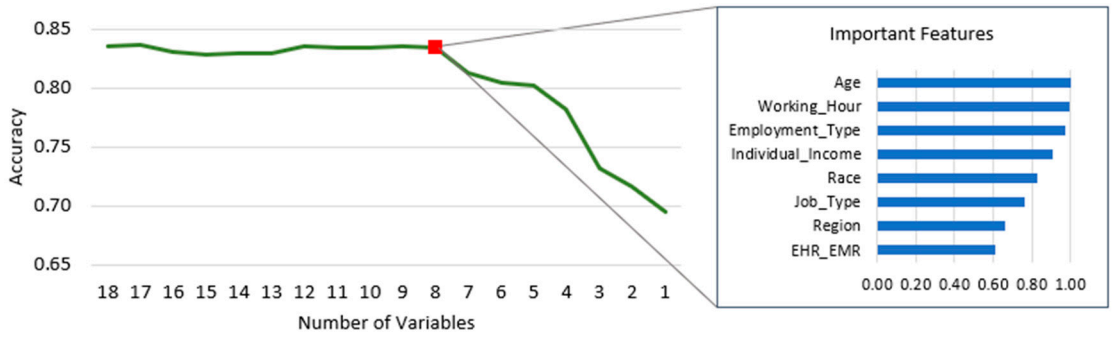

Figure 5. Optimal Number of Feature Selections Based on Minimum Accuracy.

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Table 7. The correct classification metrics with eight feature selection.

CRITERION	SMOTE_LR	SMOTE_RF	SMOTE_DT	SMOTE_XGB
ACCURACY	70.39%	82.21%	74.84%	82.19%
RECALL(SENSITIVITY)	80.91%	90.52%	55.09%	81.12%
PRECISION	70.13%	82.36%	72.70%	89.72%
F1-SCORE	75.05%	88.40%	62.62%	85.20%
AUC	73.24%	80.82%	76.29%	80.93%

4. Conclusion and Future Work

The utilization of machine learning algorithms for processing raw employee turnover data represents a promising avenue for enhancing the capacity of human resource teams to address nurse turnover effectively. Through a comprehensive analysis of the key contributing factors to nurse turnover, it is possible to implement proactive measures aimed at its mitigation, facilitated by integrating machine learning algorithms.

The present study introduces an effective and efficient machine learning algorithm designed to predict nurse turnover utilizing the 2018 National Sample Survey of Registered Nurses (NSSRN) dataset. The machine learning techniques proposed encompass Logistic Regression (LR), Random Forest (RF), Decision Trees (DT), and Extreme Gradient Boosting (XGB). To address the imbalanced datasets frequently encountered in the NSSRN dataset, we apply the Synthetic Minority Over-sampling Technique (SMOTE). None of the studies treated data imbalance problems of the NSSRN dataset when performing predictive analysis to predict nurse turnover. Our study demonstrates that by addressing the issue of imbalanced datasets through SMOTE. This novel methodology effectively mitigates dataset imbalance in human resources, offering predictive insights that can empower healthcare managers and supervisors to take informed actions regarding factors influencing turnover intentions, thereby formulating intervention policies to retain their workforce.

SMOTE_RF produced variable importance scores, which calculate the relative score of the different predictive factors. From the importance of predictor variable analysis, Age, Working hours, EHR/EMR usability, individual income, and household income were among the top five priorities in predicting turnover. We also used SMOTE_DT and SMOTE_XGB approaches to find the variable importance score and a high correlation was observed among different models. Lastly, researchers used the SMOTE_LR approach to predict the turnover for comparisons with our other proposed models. Five predictive factors found in SMOTE_RF were also significant in the SMOTE_LR model. In summary, factors that reduce the likelihood of turnover include being in the NP category, residing in the South and West regions, using Electronic Health Records (EHR) or Electronic Medical Records (EMR) technology, working standard hours, having high job satisfaction, ample job practice, being of white ethnicity, holding a BSN or MSN degree, and being young with a lower individual income.

This study's results may interest healthcare managers or supervisors involved in staff management planning who wish to minimize the nurse turnover rate. The key considerations for practitioners include factors such as age, working hours, technology usability (EHR or EMR adoption), full-time versus part-time employment, geographic region, and job satisfaction. The literature consistently identifies these variables as influencers of turnover intentions. For instance, prior research by Cho et al. [21] noted a negative correlation between turnover intention and job dissatisfaction, while Blytt et al. [6] observed similar findings regarding overtime.

Our study found that the age variable emerged as the most significant factor in our SMOTE_RF analysis, with a notably high turnover probability observed among younger nurses. This observation is in alignment with the findings of several previous studies [6], [8], [21], [30], all of which have highlighted age as a major determinant influencing nurse turnover. The inclination for younger nurses to exhibit higher turnover rates can be attributed to various factors. New graduate nurses and those in the early stages of their careers often depart their current positions in pursuit of better career prospects or improved employment benefits, such as higher income or more favorable job conditions [38]. Understanding that age plays a pivotal role in nurse turnover allows us to consider it a potentially controllable factor within the healthcare sector. Proactive measures should be

implemented by supervisors and managers to address this issue and mitigate the turnover intention among younger nurses. These measures may include offering comprehensive job training, providing ample opportunities for on-the-job practice, and carefully assigning patients to new nurses who require additional time to acclimate to their new work environment. By taking such actions, healthcare institutions can better retain their younger nursing staff and ensure the continued delivery of high-quality patient care. This proactive approach acknowledges the significance of the age variable in nurse turnover and leverages it as a strategic point of intervention.

The second most crucial variable in our study is the "Working Hours," specifically the impact of overtime on nurse turnover. Our findings underscore the substantial influence of overtime on the turnover rates among nurses, emphasizing the importance of addressing this issue. This insight can serve as compelling evidence to inform the development of optimal work scheduling practices and guidelines for nurse work scheduling aimed at minimizing nurse turnover, as advocated by Bae [8]. Overtime hours must be closely regulated to prevent nurse burnout, ensuring they can maintain their well-being and consistently deliver high-quality patient care. A key aspect of this regulation is continuously monitoring work hours and overtime. This monitoring should be a fundamental part of maintaining the quality of work within healthcare institutions [31]. It is particularly crucial during shift changes when uncertainties in hospital operations can result in unexpected overtime. Robust policies need to be established during shift changes to address this challenge effectively, and supervisors or managers should actively advocate for implementing such policy changes. These measures are vital in maintaining a healthy work-life balance for nurses and ultimately contribute to reducing turnover rates, thereby enhancing the overall quality of healthcare services.

Our findings also underscore the strong association between nurses' use of EHR or EMR technology and turnover intentions [35]. In the United States, gray literature has reported higher job satisfaction among nurses using EHR systems. Nevertheless, issues such as poor EHR usability, the lack of standards, limited functionality, and the need for workarounds can detrimentally impact nurse productivity, patient care, and outcomes, as reported by Bjarnadottir et al. [36]. Adequate information and support are crucial to minimize potential harm caused by suboptimal EHR systems, as such improvements can enhance patient-nurse interactions and job performance, reduce medical errors, and alleviate nurse burnout and stress. Continuous support, financial incentives, and adherence to best practices should be integral components of the strategy to ensure the successful implementation of EHR or EMR systems in healthcare settings.

Finally, the nature of a nurse's employment, whether full-time or part-time, significantly influences nurse turnover rates. Part-time nurses tend to exhibit a higher likelihood of turnover. This phenomenon can be explained by the practice of assigning part-time nurses to fill in for their full-time counterparts. Consequently, part-time nurses may find themselves less familiar with the routines, daily operations, and processes of the hospital wards or units, leading to apprehension about their work in the hospital setting. To address this issue and mitigate the fear of work among part-time nurses, implementing a buddy system could be an effective strategy [34]. This system would pair part-time nurses with more experienced and seasoned counterparts, providing them with the necessary support and guidance. Such a support system can go a long way in helping part-time nurses acclimate to their work environment and foster a sense of confidence and belonging within the hospital. Regardless of working environment, salary, region, and job satisfaction can also be considered to reduce nurse turnover.

Our machine learning analysis has underscored the enhanced predictive power of SMOTE_RF when the number of variables is streamlined. This finding highlights the importance of prioritizing essential features and avoiding unnecessary information when addressing nurse turnover through interventions led by human resource teams, supervisors, or managers. Notably, SMOTE_RF consistently outperformed alternative methods across all performance metrics considered in this study.

While our study yielded favorable results, there are still several limitations. The analysis primarily focused on the working environment and individual characteristics, largely due to constraints imposed by the NSSRN dataset, which offered limited survey data results. Factors like

leadership style, communication with management, individual health status, and collaboration with colleagues, which could significantly impact nurse turnover, were not incorporated into the model [3], [11]. Future research should include these additional variables to ensure a more comprehensive analysis. Furthermore, researchers should explore alternative class imbalance methods beyond those employed in our study, as some of these approaches may offer more advanced and effective ways to examine nurse turnover. Researchers must also apply more sophisticated sampling techniques to address imbalances in predictive variables, a limitation present in our current study. By addressing these limitations and adopting more comprehensive methodologies, we can further enhance our understanding of nurse turnover dynamics and contribute to developing more effective intervention strategies.

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