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Identification of important factors in an inpatient fall risk prediction model to improve the quality of care using EHR and electronic administrative data: A machine-learning approach

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Abstract

Background: Inpatient falls, many resulting in injury or death, are a serious problem in hospital settings. Existing falls risk assessment tools, such as the Morse Fall Scale, give a risk score based on a set of factors, but don't necessarily signal which factors are most important

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Declaration of Competing Interest
The authors report no declarations of interest.

Appendix A. Supplementary data
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for predicting falls. Artificial intelligence (AI) methods provide an opportunity to improve predictive performance while also identifying the most important risk factors associated with hospital-acquired falls. We can glean insight into these risk factors by applying classification tree, bagging, random forest, and adaptive boosting methods applied to Electronic Health Record (EHR) data.

Objective: The purpose of this study was to use tree-based machine learning methods to determine the most important predictors of inpatient falls, while also validating each via cross-validation.

Materials and methods: A case-control study was designed using EHR and electronic administrative data collected between January 1, 2013 to October 31, 2013 in 14 medical surgical units. The data contained 38 predictor variables which comprised of patient characteristics, admission information, assessment information, clinical data, and organizational characteristics. Classification tree, bagging, random forest, and adaptive boosting methods were used to identify the most important factors of inpatient fall-risk through variable importance measures. Sensitivity, specificity, and area under the ROC curve were computed via ten-fold cross validation and compared via pairwise t-tests. These methods were also compared to a univariate logistic regression of the Morse Fall Scale total score.

Results: In terms of AUROC, bagging (0.89), random forest (0.90), and boosting (0.89) all outperformed the Morse Fall Scale (0.86) and the classification tree (0.85), but no differences were measured between bagging, random forest, and adaptive boosting, at a p-value of 0.05. History of Falls, Age, Morse Fall Scale total score, quality of gait, unit type, mental status, and number of high fall risk increasing drugs (FRIDs) were considered the most important features for predicting inpatient fall risk.

Conclusions: Machine learning methods have the potential to identify the most relevant and novel factors for the detection of hospitalized patients at risk of falling, which would improve the quality of patient care, and to more fully support healthcare provider and organizational leadership decision-making. Nurses would be able to enhance their judgement to caring for patients at risk for falls. Our study may also serve as a reference for the development of AI-based prediction models of other iatrogenic conditions. To our knowledge, this is the first study to report the importance of patient, clinical, and organizational features based on the use of AI approaches.

1. BACKGROUND AND SIGNIFICANCE

Patient falls are a leading cause of human injury and mortality across international hospital settings [1–4]. It is estimated that in the United States (US) one million falls occur in hospitals annually, with an associated direct medical cost of $50 billion [5,6]. Fifty percent of inpatient falls result in injury, ten percent result in severe injury, and one percent result in death [7,8]. Patient falls can be largely prevented if important factors associated with these adverse events are known [9].

Risk of fall is commonly measured using assessments such as the Morse Fall Scale, the St. Thomas’s risk assessment tool in falling elderly inpatients (STRATIFY), and Hendrich’s High-Risk Fall Model [10–12]. These tools require clinician time for assessment and manual data entry, contributing to the clinician documentation burden [13,14].

These instruments have low specificity, which cause difficulty in determining how to focus fall prevention tactics in the hospital setting [15]. Furthermore, the few features captured in these assessments focus primarily on intrinsic risk factors and are constrained by contemporaneous clinical and methodological knowledge of the 1980s and 1990s. Advancements in data science have strengthened investigators' ability to use data captured from electronic health records (EHRs) and electronic administrative systems to identify robust prediction models [16].

The volume of clinical and administrative data captured in hospital systems is growing in electronic systems during routine patient care [17]. This data offers opportunities to improve the quality of inpatient care and fall prevention practices [18]. Many features could exist in these data to identify a generalizable fall prediction model. Decreases in fall rates have mostly been modest in hospitals and this type of data offers much promise [19,20]. However, large amounts of data can pose methodologic challenges with the use of traditional statistical approaches that are typically applied when testing the effects of a few features. When assumptions of traditional statistics cannot be met, machine learning techniques are able to screen a multitude of factors from big data and are capable of handling nonlinear interactions [21].

Advances in computing technology can increase the prospects of utilizing EHR and electronic administrative data to identify hospitalized patients at risk of falling, without added burden on clinicians [22,23]. Machine learning methods, including random forest and adaptive boosting, have emerged as powerful techniques that can accurately predict clinical outcomes and identify important predictors [24–26]. An advantage of these tree-based methods is that they are easily explained compared to other AI methods such as deep learning [27]. Robust model validation techniques like cross-validation can help generalize the prediction error on unseen data [28]. While fall prediction statistical models exist, their use is limited by the bias attributed to inadequate sample sizes, missing data, and not accounting for overfitting in models [29–36]. Automated methods such as machine learning can identify unknown plausible factors that could explain more fully the mechanisms of patient falls.

The objective of this study was to apply automated machine learning methods to identify the importance of known and unknown hospital inpatient fall risk factors, while also validating prediction performance of models on training and testing data sets.

2. MATERIALS AND METHODS

2.1. Study Setting, Design, and Ethical Considerations

This study used EHR data from the University of Florida's (UF) Integrated Data Repository (IDR) and administrative records from UF Health Shands (curated by QuadraMed Co., Plano, TX). We included 14 medical/surgical units of a tertiary care hospital in the southeastern US. EHR and administrative data was collected between January 1, 2013 and October 31, 2013 for patients who were at least 21 years of age on January 1. We excluded 14 patients who were hospitalized on a transition unit.

This case-control study identified risk factors for patient falls. Cases were all patients who experienced a fall event during hospitalization. Controls were patients who did not experience a fall event during their hospitalization but were at risk of falling. Each case was matched with two randomly selected controls that overlapped on at least one day of hospitalization. Risk of falls was measured by the Morse Fall Scale, which has been demonstrated to be reliable [38,39].

This study was approved by the Institutional Review Board of the University of Florida (protocol #201600423). The original data was de-identified in compliance with the US Health Insurance Portability and Accountability Act (HIPAA) [40]. Expert determination was used for the HIPAA-anonymization method [41].

2.2. Model Predictors and Outcome

UF Health's electronic incident reporting system was used to validate patients who fell during their hospitalization. For patients with multiple fall events, one was randomly chosen, which may have occurred over multiple admissions during the study timeframe. Variables included patient characteristics (e.g., age and sex), admission information (e.g., hospital unit), assessment information (e.g., the Morse Fall Scale and mobility assessment), clinical data (e.g., the Charlson Index), and staffing information (e.g., registered nurse staffing). Missing values were imputed. This study is an extension of the work of Choi et al. by adding the Charlson comorbidity index, nurse skill mix, percentage of nurses certified, percentage of nurses with a bachelor's degree or higher, weekday/weekend shift, day/night shift, middle/end of a shift, and the nurse staffing ratio [37]. A list of variables used in this study are listed in Table 1 and their definitions are in Lucero [42].

In this study, we applied tree-based, machine learning methods (a single classification tree, bagging, random forest and adaptive boosting) to identify the features most predictive of patient falls [43–47]. The Gini index was used for the single classification tree to identify the hierarchical structure of important features. We also calculated the variable importance values of all features used by bagging, random forest, and boosting methods, and listed the important features. For the bagging and random forest approaches, the permutation importance of all features was measured as a proportion of the largest value [45]. For adaptive boosting, the relative influence of all features was measured as a proportion of the largest value [48]. A description of each machine learning method and the variable importance assessment is provided in Appendix A. We compared the performance of the machine learning methods to a univariate logistic regression statistical model for the Morse Fall Scale score. To account for the possibility of multicollinearity among hospital units, we compared the of a multivariate regression model of all features to both a random effects model and a generalized estimating equation multivariate regression model.

We produced the Receiver Operating Characteristic (ROC) curve for each of the four tree-based models as well as the Morse Fall Scale total score. We also calculated the sensitivity, specificity, the Area Under the Receiver Operating Characteristic (AUROC) curve, and their respective confidence intervals using ten-fold cross validation. These statistics were calculated at the cut-points of the ROC curves based on the Youden Index [49–51]. Pairwise t-tests were used to assess differences in the sensitivity, specificity, and the AUROC curves among the predictive models. The t-tests were corrected to account for the bias in Type I error when applied to cross validation techniques [52]. All comparisons were made at a p-value of 0.05.

In order to determine which variables were the most important features selected for each of the machine learning models, we compared the AUROC of the full model to the same machine learning technique with only the K variables with the highest variable importance measure. A t-test was performed to compare the AUROC measures. We reported the smallest K for which there was no difference in AUROC between the models containing all 38 features and the models containing only the K variables with the highest variable importance measure.

All statistical analyses and graphs were generated using R (version 3.5.1) [53].

3. RESULTS

We identified a total of 272 patients who fell (cases) and matched them to 542 patients who did not fall (controls) during their hospitalization. A set of 38 patient, clinical, and administrative features were included with each of the machine learning methods. Hemoglobin level was the only feature with missing data, which comprised 3.7% cases and 4.2% controls. The median hemoglobin level was imputed for missing values. Overall summary statistics are provided in Table 1, and described by unit in Appendices C1 – C14 of the Supplementary Materials.

3.1. Analysis of important factors

Fig. 1 depicts the results of the single classification tree analysis. Six features were automatically selected for the hierarchical structure. The features in descending order included history of falls, Morse Fall Scale total score, age, percentage of registered nurses with specialty certification, mental status, and number of high risk fall risk increasing drugs (FRIDs).

Variable importance graphs for bagging, random forest, and adaptive boosting methods appear in Fig. 2. Based on the results of the t-test to compare AUROC between the models with all 38 variables and the models containing only the K variables with the highest variable importance measure, the bagging and boosting methods had a minimum of 4 important features and the random forest method had a minimum of 6 important features that did not show a difference in AUROC. Among the top features, history of falls exhibited the greatest relevant importance to patient falls across the three approaches. Patient's age and Morse Fall Scale total score were important in all three approaches. Mental status was important in two of the models, while Morse Fall Scale gait/transferring, and hospital unit type, and the number of high risk FRIDs were important in one. The variable importance measures of all 38 variables for each of the three methods are provided in Appendix B.

3.2. Model evaluation

The sensitivity, specificity, AUROC, and each of their 95% confidence intervals for each predictive model are presented in Table 2. The bagging approach yielded the most sensitive model (0.79) while the Morse Fall Scale total score resulted in the least sensitive model (0.58). On the other hand, the Morse Fall Scale total score produced the most specific model (0.87) followed by adaptive boosting, random forest, bagging, and the single classification tree (i.e., 0.86; 0.86; 0.84; and 0.78, respectively). In terms of AUROC (Fig. 3), the random forest method showed the highest discriminatory ability (0.90) followed by adaptive boosting, bagging, the Morse Fall Scale total score, and finally the single classification tree (i.e., 0.89; 0.89; 0.86; and 0.85, respectively). Based on the pairwise comparisons we conducted to evaluate the performance measures among the five approaches, the Morse Fall Scale total score was lower than each of the other four methods in terms of sensitivity, and lower than the three forest based methods (bagging, random forest, and boosting) in terms of AUROC. The single classification tree model was lower than each of the four other predictive models in terms of specificity, and lower than the three forest based methods in terms of AUROC. The single classification tree predictive model and Morse Fall Scale total score had the poorest performance in terms of discriminatory ability. Finally, the Morse Fall Scale total score had the lowest sensitivity.

There were no differences between the main effects models and the random effects and generalized estimating equation multivariate models.

4. DISCUSSION

This study investigated AI techniques to detect and rank important predictive factors of hospitalized patient falls. Additionally, we produced cross-validated prediction models from EHR and administrative data that identify risk of falls based on easily obtainable patient, clinical, and organizational factors. Building on the advantages of organizational investments and computing technologies, the prediction models have the potential to support healthcare provider and organizational leadership decision-making that results in improved quality of care.

There is growing interest in using EHR data for clinical outcome prediction, but the context in which these data are generated could also exert influence on the quality of patient care outcomes [23]. Nonetheless, EHR data can be better suited for using AI to predict clinical outcomes. An advantage of EHR data is its size. EHR data provides opportunities to improve the quality of care by examining simultaneously multiple related outcomes, for example heart failure, 30-day readmission, stroke, and diabetes readmission [56–59]. EHR data also provides access to many predictor variables, which opens the prospects of observing changes in patients and care over time. Another key benefit is that EHR data contains many observations that can could be used as prediction model validation datasets. There are also pitfalls in using EHR data including missing data and informative presence [60–62]. Hospital systems are increasingly storing EHR data which can be used to facilitate studying rare events, such as patient falls. In this study, we analyzed 30 features from EHR and 8 features from administrative data among 814 hospitalized patients who fell and did not fall during their admission. Three AI models (i.e., bagging, random forest, and adaptive boosting) exhibited satisfactory performance in predicting patient falls and warrant further testing to establish external validity.

Given the advantages of EHR data and feasibility of AI techniques, we considered multiple interactions among features. Previous studies of patient fall prediction have primarily considered individual patient characteristics and conventional risk assessment tools with few interaction terms [10–12]. However, researchers have documented various independent relationships between nursing care and hospital patient falls [63–67]. Several features, including mental status and number of high risk FRIDs, were important across the prediction models and could be managed through clinical care and nursing unit management. We have shown that bagging, random forest, and boosting have a substantially higher ability to identify fallers over the Morse Fall Scale total score. Robust prediction models identify patients at varying degrees of risk would be of great clinical significance. With the disproportionate growth of older adults, one in five Americans will be at least 65 by 2030, and will occupy the most hospital beds on any given day [68,69]. Although AI risk prediction models cannot currently replace clinical judgment, these tools could provide immediate information to avoiding falls at critical stages of deterioration or increased environmental safety hazards [42,70].

To better understand patient fall risk and improve the interpretability of the prediction models, we ranked all features in this study, and reported the most important according to their contribution to predicting falls. Among these features, history of falls, age, Morse Fall Scale total score, mental status, unit type, gait/transferring and the number of high risk FRIDs were the most relevant factors across bagging, random forest, and boosting. While some of these factors have been identified as predictors of patient falls in previous studies, there is still room to learn whether a patient's mental status, score of a Morse Fall Scale assessment, and the number of high risk FRIDs they are taking are valid predictors of falls when hospitalized on a medical or surgical nursing unit. It's worth noting that existing fall risk assessments do not contain all the items identified in our list of important features (such as age, unit type, FRIDs, and impaired mental status) [10–12]. Validation of accurate prediction models that combine simple and interpretable assessment tools with high performance contemporary machine learning methods can provide valuable clinical decision support, including prioritizing of fall prevention interventions and resources in medical and surgical nursing units.

Advances in computing technology and the availability EHR and administrative data presents opportunities to prevent and reduce patient falls through a learning health system [71,72]. A learning health system can result in personalized clinical care and quality improvements by learning throughout the delivery of care. Fall risk could be automatically measured when features change during a patient's admission. While ideas of learning health systems have been discussed, little evidence exists on the implementation or impact of such a system [73]. Among use cases, there have been efforts to improve the quality of care for pediatric patients suffering from Crohn's disease and cerebral palsy, optimize care delivery for palliative care and lung cancer patients, and reduce missed primary care appointments [74–78]. Most healthcare systems lack the infrastructure to support these components reliably and efficiently [79]. However, requirements for knowledge generation to improve the quality of care include reliable data capture and analysis methods that can yield timely feedback of knowledge to the system [79].

There are limitations that should be discussed before applying in clinical practice. Regarding study design, the investigation was limited to data from one hospital setting. Cross-validation can be affected by population bias. Testing our models on data from other hospitals is needed to establish external validity. Secondly, the Morse Fall Score was used to measure fall risk. Not all hospitals use this assessment, which may hinder generalizability to all hospital settings. Thirdly, this study focuses on all inpatients who are at risk for falls, not just first time fallers. This presents an opportunity to conduct additional research to identify the risk factors associated with first time inpatient fallers. Fourthly, although we identified models with relatively stable performance, sensitivity, specificity and AUROC, estimates were subject to case-control study design. The model performance tests would be best performed with a population sample, which would reflect the true calibration and discrimination of the prediction model. Although it is possible to re-weight the sample of the case-control to match the prevalence of falls to the population, this prevalence varies widely across hospital populations [80–85]. The results for the bagging, random forest, and adaptive boosting algorithms are subject to variability in sensitivity and specificity measures due to using a binary classifier. Instead, it would be ideal to use a probability classification scheme [86]. In terms of AI techniques, the automated feature selection methods from machine learning models may fail in determining the true causal variables, not being able to identify confounders [87]. Even if the prediction model includes actionable features, their applicability in practice (not only prediction) may not be recommended without prospective testing or further causal analysis on observational data, e.g. defining a causal structure for variables. Finally, organizational differences can also influence how patient and clinical data are recorded in the EHR and administrative data by healthcare providers.

In summary, this preliminary study established cross-validated prediction models based on analyses of 38 individual, clinical, and organizational features. Our findings are of great clinical and organizational importance because we identified relevant and novel factors for hospital patient fall prediction. The prediction models have the potential to support personalized care and improve the quality of patient care by complementing health care provider’s judgment and decision making. Specifically, nurses could assist patients directly, such as improving mental status or administering fall risk inducing drugs, to effectively reduce fall risk. More broadly, our study may provide a reference for the development of AI-based prediction models that are modifiable by health care providers and leaders.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Summary Points

What was known:

- Existing fall risk prediction methods, such as the Morse Fall Scale, do not fully capture all risk factors associated with inpatient falls.
- Electronic Health Record (EHR) data has the potential to be used to identify the most important factors of inpatient falls via machine learning methods.
- Few existing studies have applied artificial intelligence (AI) to determining the most important factors of inpatient falls.

What we add:

- Tree based artificial intelligence methods can effectively determine the most important factors of inpatient falls via variable importance measures.
- Equipped with the knowledge of these additional factors of inpatient falls not found in the existing fall risk prediction tools, nurses can better care for their patients and effectively reduce the number of falls in the hospital setting.
- This study can serve as a reference in the development of AI-based prediction models of other iatrogenic conditions.

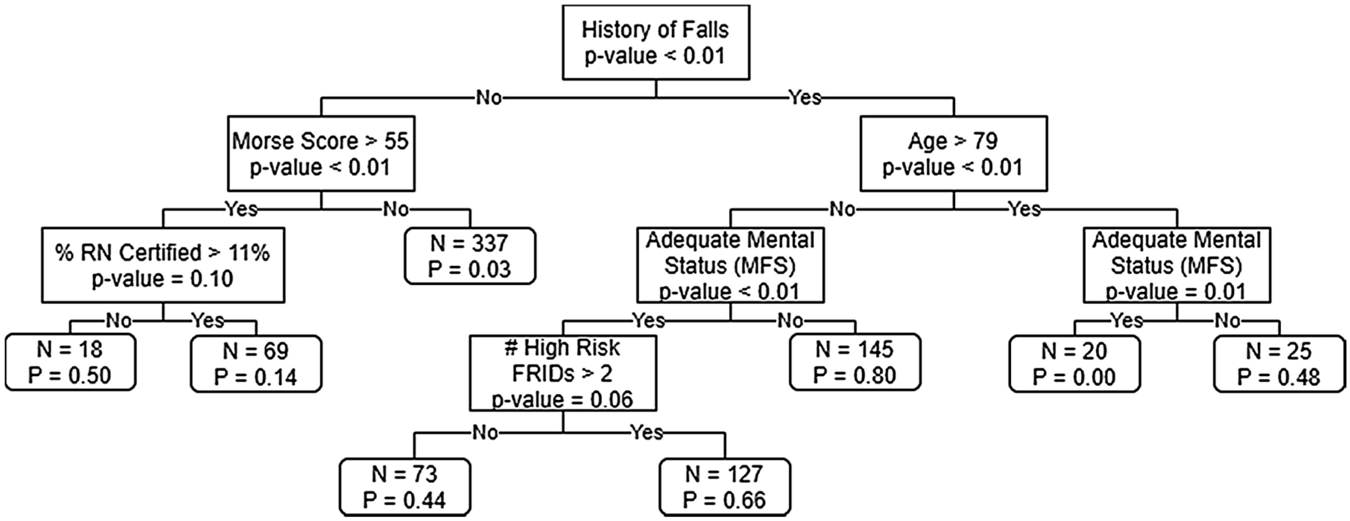

Fig. 1.

Classification tree of fall risk factors and number of patients affected at each node.

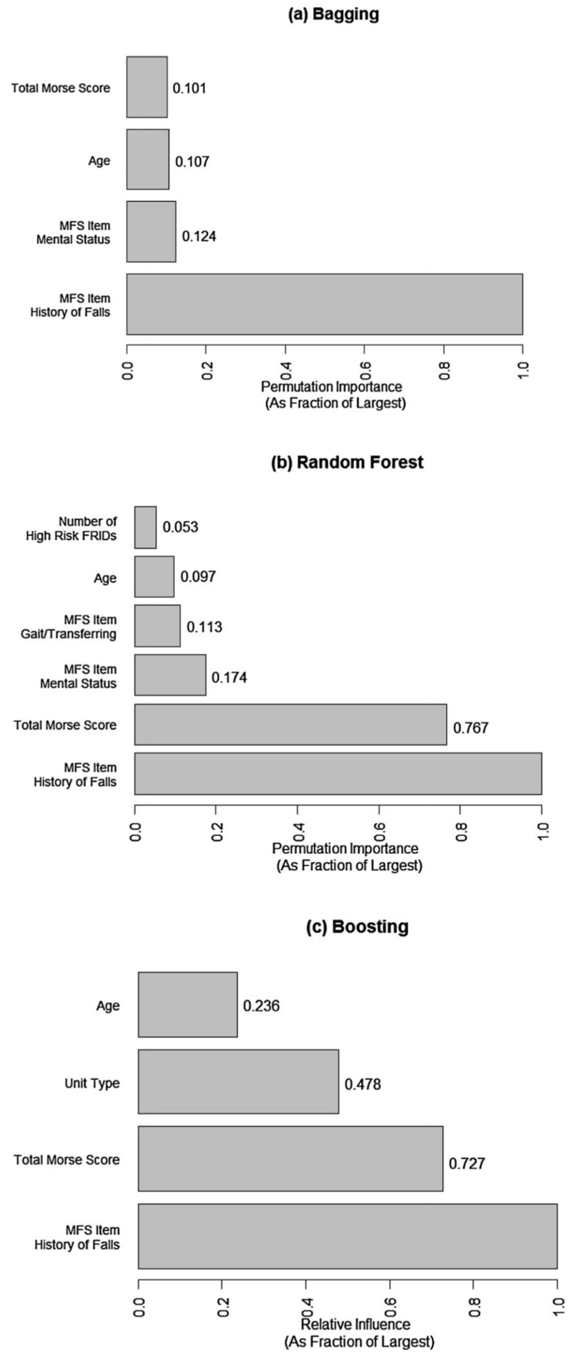

Fig. 2.

Variable importance graphs of the most important features for bagging, random forest, and adaptive boosting tree-based machine learing methods

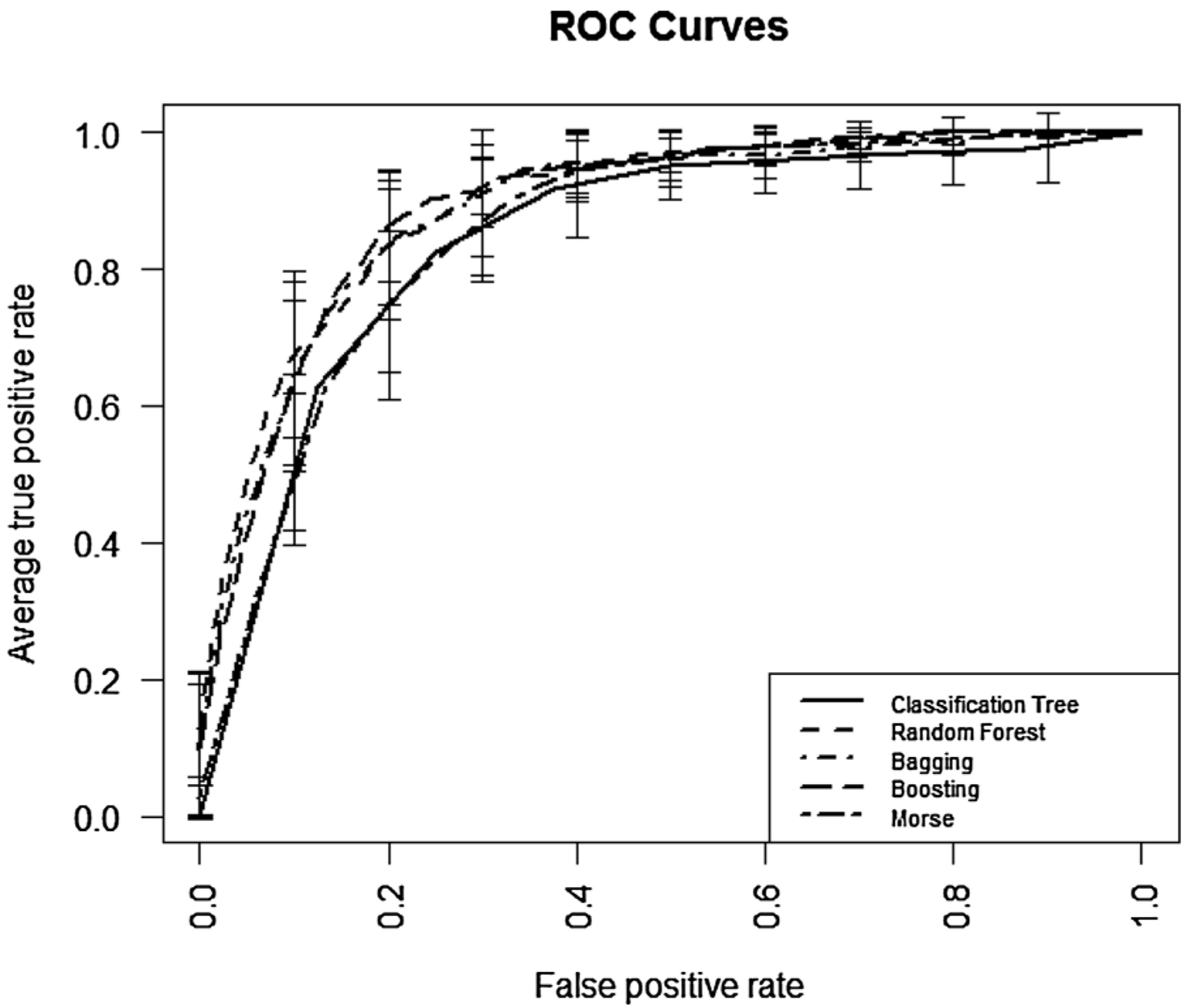

Fig. 3.

ROC curves for single classification tree, random forest, bagging, adaptive boosting and Morse Fall Scale total score prediction models.

Table 1

Distribution of patient, clinical, and organizational features among fallers, non-fallers, and both fallers and non-fallers

Item	Fallers (n = 272)	Non-Fallers (n = 542)	Total[a] (n = 814)
Patient Characteristics, n (%)			
Male	139 (51%)	258 (48%)	397 (49%)
Age (Mean, SD)	56.8 (14.9)	58.3 (17.0)	57.8 (16.3)
Medications, n (%)			
High dose of high risk FRIDs[b]	121 (44%)	138 (25%)	259 (32%)
Number of high risk FRIDs[b] (Mean, SD)	4.9 (4.1)	3.4 (3.5)	3.9 (3.8)
Morse Fall Scale (MFS), n (%)			
History of falls	244 (90%)	146 (27%)	390 (48%)
Presence of a secondary diagnosis	263 (97%)	496 (92%)	759 (93%)
Ambulatory aids			
Crutches, cane, or walker	87 (32%)	87 (16%)	174 (21%)
Furniture	13 (5%)	6 (1%)	19 (2%)
Use of a IV/Heparin lock	264 (97%)	516 (95%)	780 (96%)
Gait/Transferring			
Weak	153 (56%)	162 (30%)	315 (39%)
Impaired	59 (22%)	55 (10%)	114 (14%)
Impaired mental status	136 (50%)	88 (16%)	224 (28%)
MFS total score (Mean, SD)	79.3 (17.0)	51.3 (19.7)	60.7 (23.0)
Medical Conditions and Indicators of Health Status, n (%)			
Heart failure	92 (34%)	172 (32%)	264 (32%)
Visual or language impairment	43 (16%)	35 (6%)	78 (10%)
Hypoglycemic event	17 (6%)	26 (5%)	43 (5%)
Uncontrolled diabetes mellitus	38 (14%)	42 (8%)	80 (10%)
Impaired Mobility	204 (75%)	398 (73%)	602 (74%)
Confusion	111 (41%)	88 (16%)	199 (24%)
Alcohol withdrawal	17 (6%)	9 (2%)	26 (3%)
Hemoglobin Level (g/dL) (Mean, SD)	10.4 (2.2)	11.1 (2.3)	10.8 (2.3)
Orthopedic surgery	6 (2%)	18 (3%)	24 (3%)
Hypotension	56 (21%)	99 (18%)	155 (19%)
Physical Therapy initiation	139 (51%)	148 (27%)	287 (35%)
Charlson Comorbidity Index[c] (Mean, SD)	3.5 (3.1)	2.6 (2.8)	2.9 (2.9)
Dizziness or Vertigo	33 (12%)	46 (8%)	79 (10%)
Hallucinations[f]	—	—	—
Visual Impairment	5 (2%)	16 (3%)	21 (3%)
Hearing Loss	18 (7%)	11 (2%)	29 (4%)
Language Impairment	20 (7%)	19 (4%)	39 (5%)

Item	Fallers (n = 272)	Non-Fallers (n = 542)	Total[a] (n = 814)
Parkinson's Disease[f]	—	9 (2%)	10 (1%)
Seizure Disorders	60 (22%)	50 (9%)	110 (14%)
Organizational characteristics			
Hospital Unit Type, n (%)			
Cardiology/CV telemetry	20 (7%)	69 (13%)	89 (11%)
Medicine 1	25 (9%)	44 (8%)	69 (8%)
Medicine 2	29 (11%)	52 (10%)	81 (10%)
Medicine 3	34 (13%)	39 (7%)	73 (9%)
Medicine 4	15 (6%)	61 (11%)	76 (9%)
Vascular/ENT/Tele medicine	18 (7%)	50 (9%)	68 (8%)
Neurology/Burn/Plastics/GI medicine	27 (10%)	43 (8%)	70 (9%)
Neurosurgery	31 (11%)	34 (6%)	65 (8%)
Oncology	11 (4%)	20 (4%)	31 (4%)
Bone marrow transplant	12 (4%)	14 (3%)	26 (3%)
Trauma/Lung transplant	14 (5%)	31 (6%)	45 (6%)
Orthopedics	12 (4%)	30 (6%)	42 (5%)
General/GI surgery	10 (4%)	25 (5%)	35 (4%)
Urology	14 (5%)	30 (6%)	44 (5%)
Nurse Skill Mix[d]	71%	72%	71%
Percent Nurses Certified	22%	23%	23%
Percent Nurses with Bachelor of nursing	48%	47%	47%
Weekday (Weekday vs. Weekend shift)	205 (75%)	417 (77%)	622 (76%)
Day (Day vs. Night shift)	138 (51%)	304 (56%)	442 (54%)
Middle of Shift (Middle vs. End of shift)	135 (50%)	260 (48%)	395 (49%)
Staffing Ratio[e]			
0.95 < Ratio < 1.05 [Baseline]	60 (22%)	135 (25%)	195 (24%)
Ratio < 0.85	68 (25%)	139 (26%)	207 (25%)
0.85 < Ratio < 0.95	69 (25%)	140 (26%)	209 (26%)
Ratio > 1.05	75 (28%)	128 (24%)	203 (25%)

[a] Fallers and Non-Fallers.

[b] FRID: Fall risk increasing drug.

[c] As calculated in Charlson and Quan [54,55]

[d] Calculated as the proportion of registered nurses on a shift

[e] Calculated as the ratio of actual registered nurses to the recommended registered nurses on a shift

[f] Cell counts with an en-dash indicate a count less than 5

Table 2

Sensitivity, Specificity, AUC and Calibration Cutoff Probability

Statistic (95% Confidence Interval)	Bagging	Random Forest	Adaptive Boosting	Classification Tree	Morse Fall Scale Total Score
Sensitivity	0.79 (0.73, 0.84)	0.73 (0.68, 0.79)	0.74 (0.68, 0.81)	0.78 (0.66, 0.89)	0.58 (0.52, 0.65)
Specificity	0.84 (0.80, 0.87)	0.86 (0.82, 0.89)	0.86 (0.82, 0.90)	0.78 (0.72, 0.84)	0.87 (0.83, 0.91)
AUROC	0.89 (0.85, 0.92)	0.90 (0.87, 0.92)	0.89 (0.87, 0.91)	0.85 (0.81, 0.89)	0.86 (0.83, 0.88)
Calibration Cutoff Probability[a]	0.42	0.39	0.35	0.37	0.26

[a]Point that maximizes Youden's J statistic