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Developing Risk Assessment Tool for Patients' In-Hospital Falls Using Predictive Modeling

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1 Abstract

Inpatient falls are a serious cause of fatal and non-fatal injuries among patients of all ages leading to disability and stillness. The post-fall treatment comes with rising medical costs and a stressful recovery phase. The present assessment tools align with analyzing causes of falls from historical data instead of present conditions. The key focus area of this research is to develop general-purpose fall risk assessment tools using machine learning-based predictive modeling. We used performance metrics to compare the accuracy and suggest the best suitable model for each shift. This general-purpose fall risk assessment tool can be used for all age groups in the diverse practice setting in hospitals. Considering the gap between the ideal fall risk assessment tool and conventional tools, our study includes factors such as etiology of falls, intrinsic, extrinsic, and situational risk factors. The analysis of patient falls will provide information to clinicians and guide them in developing intervention strategies for patients. A solid initiative to prevent falls and a tool that offers precise risk scores are critical pieces for improving outcomes of falls. Our research work has the potential to motivate the development of a general-purpose, highly accurate, and practical tool that can successfully determine an individual's risk score.

2 Introduction

Inpatient falls are the most commonly reported safety incidents in hospitals. The post-fall treatment comes with rising medical costs and a stressful recovery phase. It is a significant set of concerns among all the hospitals in the US. Falls are a serious cause of fatal and non-fatal injuries among patients of all ages leading to disability and stillness. Therefore, addressing fall prevention and prediction is a need of an hour [1,2]. The basic understanding of the term “inpatient falls” is understood simply as a slip or trip faced by a patient. However, it can also be studied in a more detailed manner concerning physiological imbalance [2]. A wide range of classifications and definitions have been provided in several studies, which had a common goal of developing intervention strategies to prevent falls [2]. There are considerable differences and thus fail to provide a standard definition that can be used for a general description of falls [3].

A very early definition of falls states that “imbalance of the vertical line that passes through the center of the human body mass falls beyond the base of support and correction does not occur in time” [4]. This definition is expressed in mechanical terms, but a more practical-oriented description is always better to use in research studies [5]. In most epidemiological studies, falls are defined as an unintentional action involving falling the person on ground level [5]. However, different types of approaches exist to represent falls concerning behavioral and topographical components. As a result, a general definition is always preferred, as put forward by one of the research groups called the ProFaNE group, it describes fall as “an event having unexpected outcome where the participant rests on the lower level of ground that is the floor or any other surface” [2]. This study is focused on inpatient falls that occur in healthcare settings and strategies to prevent them in the future. To understand the severity of falls, it's essential to look at the fall statistics among hospitals based on well-known publications.

2.1 Fall Statistics

Based on the Agency for Healthcare Research and Quality (AHRQ) data, nearly one million hospitalized patients fall each year in US hospitals [6]. According to the Office of the Inspector General report of 2014, 10% of Medicare skilled nursing facility residents faced severe injury resulting from falls, and 50% out of 1.6 million nursing home residents fall each year [7]. As per US Centre for Disease Control and Prevention (CDC), every 11 seconds, an adult patient is treated due to a fall injury in an emergency room. Every 19 minutes, a fatality occurs for elderly patients [8]. Many inpatient falls are highly injurious thus, increasing the overall medical cost.

In some cases, reimbursement is not provided to the hospitals under the in-hospital patients' payment system. These falls could result in different injuries ranging from minor to moderate and severe. Post fall, the patient should be treated with immediate assistance but sometimes remain unassisted, worsening the level of injury. Thus, it is not only essential to prevent falls by implementing intervention strategies, but also these strategies must be systematically used by the hospitals. It should be noted that not all falls are preventable. For example, falls due to medication can cause sudden imbalance without prior caution. However, it is possible to detect and predict fall risk [9]. This can effectively lead to fall prevention and reduce fatality, morbidity, mortality, healthcare costs, and hospital length of stay (LOS).

2.2 Impact of Falls

Based on the levels of falls, the outcomes may have a wide range, from less severe injuries to fatalities. As per the study conducted by Oliver et al. [10], most patients find it difficult to get up without assistance. This might leave patients suffering from medical conditions like hypothermia, pressure sores, dehydration, and bronchopneumonia, especially if the patient is feeling unconscious. Inpatient falls are sometimes unassisted, and around 20% of patients are left alone on the floor for an hour or more [11]. Additionally, most patients had a history of high morbidity rates before suffering from falls [11]. In elderly patients, 50% of falls result in xminor injuries, and 10% result in significant injuries (mostly fractures) [5]. Head injury, bruises, and hip fractures are common injuries caused by falls [12]. These injuries lead to increased LOS and are the most common causes of death [13]. The fallers may also suffer from other fall-related risks apart from physical injury. A study by Brownsell and Hawley [14] suggests that falls can have adverse outcomes and affect the patient psychologically, e.g., fear of falling in hospitals. Therefore, hospital staff should treat the post-fall physical and emotional consequences. There are multiple consequences of a fall based on severity, such as physical, emotional, social, and economic consequences. We've discussed financial and emotional implications in detail.

2.2.1 Economic Loss

The financial loss due to falls is considerable and should be considered while doing research related to falls, as it affects healthcare organizations and patients alike. The falls are associated with direct and indirect costs. Direct costs include service charges for doctors, nurses, and professionals. It also accounts for medical equipment and prescription drugs. Indirect costs are associated with the long-term impact of fall injuries, such as poor quality of life and disability. According to the CDC report, direct care costs such as service charges and follow-up for medication account for $19 billion every year for people who fall. Insurance companies generally cover these costs with additional co-pay, which a patient takes care of. Additionally, direct and indirect costs are estimated to be around $54.9 billion for 2020 [15].

The prominent healthcare entities like The American Nurses Credentialing Centre, the Joint Commission (TJC), and the Centers for Medicare & Medicaid Services (CMS) focus on preventing patient-related issues especially falls and their resulting injuries. Healthcare systems must have a focused and strategic program to prevent falls to ensure patient safety. These strategies help reduce the additional burden on a physical and emotional level for patients and a financial level for healthcare administration. Identifying factors associated with patient falls is an initial and critical part of developing fall prevention strategies. Thus, our work is focused on evaluating potential environmental and physical risk factors that may increase the probability of falling.

2.2.2 Emotional Consequences

During hospitalization, a day for discharge is the most awaited day and highly anticipated by any patient. A patient also expects quick recovery and returning to everyday life to continue activities of daily living (ADL). However, any mishap can lead to increased LOS during this hospitalization phase. This increase in stay may adversely impact a patient’s mental health outcome, thus increasing more burden on self and healthcare staff. Moreover, sustaining any injury or fall during hospitalization will diminish a patient's ability to return home after being discharged. It is well known that functional mobility, falling anxiety, physical imbalance, and muscle strength are some of the top factors that directly or indirectly impact the quality of life of patients experiencing a fall in the hospital [16]. A patient might try not to discuss the emotional response with anyone as they don’t want to be overly dramatic. In such cases, acknowledging patients’ emotional needs after a fall is critical to understand that emotional response is a natural impact of falls.

Sustaining from a fall also increases the risk of suffering from another fall. Understanding the risk and providing the necessary help to patients by making better decisions or personal attention will help prevent another fall in the future. The caretakers also suffer from the anxiety of falling of their dependent. Around 58 - 66% of the caretakers reported such cases where they had great anxiety regarding their dependent suffering from a fall [17]. Studies also suggest that a fall's psychological consequences are more intensely sustained by relatives or caretakers than the patients themselves [17]. The relatives acknowledge the fear of falls after the patient’s discharge in a better way. Furthermore, increasing patient needs can lead to hospital staff not handling it efficiently due to its challenges and resource limitations [17].

2.3 Fall Risk Assessment

A fall risk assessment is used to determine the risk associated with falls, such as low, moderate, or high. If the assessment shows a patient is at high risk of falling, the healthcare staff or caregiver must suggest intervention strategies. A fall risk assessment is a standardized tool that can be used as a prerequisite to implementing an evidence-based fall prevention protocol. Some of the benefits of this tool are as follows:

- Identification of patients having a higher risk of falling
- Identification of baseline measures of patient-specific areas of risk
- Better clinical decision making
- Helps to develop preventive measures, and care plans on a personal level
- Link intervention plans to mitigate identified risk factors associated with fall

Though assessment tools are beneficial and used to a greater extent, these tools have some limitations. Generally, a care plan is developed only by considering factors in the risk assessment tool. For example, the tool may not consider the floor surface, whether rough, slippery, or wet during the patient’s fall. Therefore, a care plan may also ignore the floor surface as one of the factors that caused falls, and it’ll fail to educate patients to be mindful of the floor surface while walking/running. As there is a possibility that the care plan might miss additional factors that are not mentioned in the tool, it is essential to try to identify and cover as many risk factors as can be associated with falls.

2.4 Problem Statement

The inpatient falls are primarily unintentional and caused by numerous factors. These factors are a combination of individual and environmental conditions [18]. This unintentional event results in the patient coming to rest on the floor or another surface. As a result of falls, approximately 50% of all patients get injured, further increasing the cost of care, LOS, resources, and sometimes death [19]. Few prevention strategies to tackle falls include reducing the height of beds from the ground, calling the bell for assistance, and keeping personal items close to the patient. Hospitals have implemented various evidence-based fall prevention tools and strategies over time. However, falls are continuously reported as one of the most common high-risk and fatal events [20]. Hospitals need to perform according to the set benchmark to prevent falls and maintain safety standards. Fall assessment tools identify risk factors for falls in hospitalized patients. The organizations such as World Health Organization (WHO) have established various frameworks to address inpatient falls. The falls that cause injury needs deep knowledge, education, infrastructure, and resources to create a safe culture as a priority [21].

International Classification of Functioning, Disability, and Health (ICF), is the WHO framework used to classify health-related domains. It helps to measure health and disability at both individual and population levels. Fall risk in most fall risk assessment tools is not aligned with the ICF framework. Also, there is a shortage of information about fall risk assessment, mainly in the case of community-dwelling older adults [22]. The community-dwelling older adults are individuals living outside of nursing homes, 65 or older. Additionally, the fall risk assessment should be diverse, and data should be collected from different disciplinary backgrounds to determine the fall-related factors. Although these tools focus more on the hospital setting, future research should also focus on community-dwelling aspects [23].

3 Literature Review

Due to the growing statistics of fall-related injuries and death, researchers are developing efficient strategies. On the other hand, healthcare organizations implement various prevention interventions to mitigate fall risk. There are numerous guidelines related to clinical practice; various screening and assessment techniques are available. These are primarily based on lagging indicators that are past data of an individual's health and not on real-time activities.

The healthcare governing organizations like the Centers for Disease Control and Prevention, the Joint Commission, and other state Departments of Health stated that fall prevention and morbidity, and mortality related to falls is a national public plan concerning health [24]. This is considered a top priority among national-level patient care objectives of Healthy People 2020 at various places. For example, the number of emergency room visits by older adults due to falls is targeted to reduce by at least 10% through goal OA-11 [25]. The studies conducted to date suggest that older patients, especially 65 years and above, are prone to high risk for falls. It is also estimated that at least one out of four adults will sustain an annual fall [24]. Therefore, it is necessary to establish programs based on fall risk prevention that possess assessment at different levels and evidence-based practices [24]. If there is no improvement in current practices, then Houry et al. [26] suggest that the falls may reach up to 100,000 per year by 2030, and these too shall be fatal falls. Additionally, it would account for a healthcare cost of $100 billion in the US.

The national objective of Healthy People 2020 is a framework designed for assisting healthcare organizations in setting a benchmark in national healthcare practices and priorities [27]. This initiative aims to improve the quality of patients' life, reduce morbidity and mortality rates, and improve overall healthcare outcomes of the community [27]. The framework used in Healthy People 2020 will enable healthcare organizations to take a multi-purpose approach to improve healthcare outcomes by addressing the delivery, physical environment, individual behaviors at the same time [27].

Although establishing a national initiative may provide some relief and prevent patient falls, the risk of falling cannot be avoided. The report published by the Harvard Medical Practice Study II, Leape et al. [28] has mentioned that most inpatient falls were due to management errors that were preventable using medical-related technology. The recent study of Oliver et al. [29] suggests that the fall rates are between 2.9 and 13 per 1000 patient beds days. 30% of these patients extended their hospital stay because they suffered injuries requiring medical assistance. In addition to the inpatient falls, Oliver et al. [29] also mentioned that the healthcare staff experienced guilt and increased anxiety if a patient under their care fell.

The development of risk assessment tools and evidence-based practices ultimately depends on selecting factors to evaluate fall risk. According to Severo et al. [30], multiple factors contribute to the higher risk of inpatient falls. The most common causes were psychological confusion and disorientation, mobility impairments, frequent urination, and higher dosage of medications. As per Severo et al. [30], these risk factors add up cumulatively to the risks when the patient gets admitted to the hospital setting. The study has addressed that the nurses or caretakers can obtain these factors through frequent and careful patient assessment. This is to ensure improved evidence-based clinical practices [30]. The study by Dykes et al. [31] suggests that the organization has multiple benefits of using evidence-based fall prevention practices.

In many cases, patients do not believe they have a high chance of falling. Therefore, organizations can manage resources once high-risk patients are identified; this will allow nurses to provide desired education to the patient. Once the patient is educated and understands their fall risk, they tend to cooperate and follow their care plan.

Until now, the literature has discussed the emerging fall statistics, establishing a national safety program by incorporating various healthcare practices. These practices include risk assessment tools, safety standard protocols, and training initiatives. It is essential to understand various fall risk assessment tools and their significance and limitations. Although it is challenging to predict falls like the accidental falls, most of the falls are caused by a patient's physiological condition, which is known and can be expected. Thus, these tools help identify risk factors modified over time through patient treatment and care [32].

Palumbo et al. [33] mentioned that it is beneficial to have fewer variables in risk prediction tools as it may provide a precise cause of falls and better prediction value. This study proves significant for future research work and provides a foundation for other researchers. These tools are preferred over complex tools and tools with a more substantial number of variables. However, the researchers need to be cautious that less complex tools should not interfere with accuracy as it’s vital to develop a balanced tool that is both simple and accurate. During the designing phase of the predictive tool, the value and significance of each variable must be evaluated to ensure high accuracy in predicting the risk [33]. Evaluating risk assessment tools in each setting is also an important process that needs to be focused on. Research by Babine et al. [34] states that common adverse events in inpatient settings are falls that cause injury to a patient, extended stay, and increased medical costs. One of their journal articles is focused on multiple causes of falls which recommends the requirement to evaluate the effectiveness of assessment tools within the hospital setting. This study suggests that determining the specificity of required assessment may help the healthcare system reduce inpatient falls and LOS [34].

The findings of Babine et al. [34] are not limited to just the evaluation of the risk assessment tool, but researchers should also consider the validity of the same. Nunan et al. [35] state that evidence-based practice is vital for fall risk assessment. Researchers need to focus on comparing the validity of fall risk assessment tools in a given specific practice setting. Most healthcare practices are implemented based on an anecdotal basis instead of scientific evidence. For example, the New York-Presbyterian Fall Risk Assessment Tool uses only particular factors to identify the risk level for falls in hospitalized patients. Quigley [36] describes that it should be the responsibility of each organization to ensure all practices are appropriately evaluated based on actual scientific evidence and not on an anecdotal basis. Quigley [36] mentioned that practices based on scientific evidence allow healthcare staff or caretakers to analyze old practices, modify current practices, and determine new practices. However, it should be noted that new practices should be sustained over a long period based on assessment outcomes. This study also suggests that research evidence integrated with clinical expertise and patient values will help create evidence-based practices. This will ensure that clinical policies are based on current research practices and meet the changing demands of patients' populations.

The New York-Presbyterian Fall Risk Assessment Tool uses 18 specific factors and helps to identify the level of risk for inpatient falls. Four risk groups range from low to high, and the assessment outcome enables placing each patient in one of these risk groups [37]. The objective of developing the New York-Presbyterian Fall Risk Assessment Tool was to incorporate the fall risk assessment tool with the patients' electronic health records. The overall reliability and specificity of the risk assessment tool are improved because of the integration design of physical assessment with a digital collection of clinical data [37]. The theory behind the development of the New York-Presbyterian Fall Risk Assessment Tool is that the integration of data sources results in the increased reliability of the assessment results. Currie et al. [37] also mentioned that in assisting patient care issues, this is one of the examples of using informatics.

The John Hopkins Hospital fall prevention program was the main motive to develop John Hopkins Fall Risk Assessment Tool. Unlike New York-Presbyterian Fall Risk Assessment

Tool, this tool assesses an individual patient instead of integrating assessment tools with electronic health records. The John Hopkins Fall Risk Assessment Tool has approximately 76.7% sensitivities and 77.5% specificities [36-37]. This tool is paper-based and uses 11 factors to determine the relative level of risk. It has three risk groups ranging from low to high, and a patient is assigned to one of these three risk groups.

In an inpatient setting, a study has reported John Hopkins Fall Risk Assessment Tool specificity, sensitivity, and predictive value of 77.5%, 76.7%, and 77.3%, respectively [38]. The John Hopkins Fall Risk Assessment Tool has benefits over the New York-Presbyterian Fall Risk Assessment Tool. For example, adaptability can be implemented outside John Hopkins in different practice settings. Also, the John Hopkins Fall Risk Assessment Tool has been translated into various languages and implemented into hospital settings of several countries [38-39]. The research work implies that the John Hopkins Fall Risk Assessment Tool is a high-potential tool and simple to implement into different specific healthcare settings concerning patient populations.

The Morse Fall Scale (MFS) 's sensitivity and specificity are higher than other risk assessment tools. The sensitivity and specificity of the Morse Fall Scale are 78% and 83%, respectively [42]. The MFS is a risk assessment tool used to determine patients’ risk of falling. The MFS is mainly used as a standard tool to identify the likelihood of falling in facilities of long-term care as well as acute care hospitals. This tool is based on six variables, with each variable having its numerical score. The variables of MFS are a history of falling with (score of 0 or 25), secondary diagnosis (score of 0 or 15), ambulatory aid (score of 0, 15, or 30), intravenous therapy (score of 0 or 20), gait (score of 0, 10, or 20), and mental status (score of 0 or 15) [43]. The overall points are calculated, ranging from 0 to 125 on the completion of the assessment. A patient is associated with low fall risk with an overall score of 0-24, a moderate risk with a 25-50, and a high risk with a score of 51 or greater. A study by Yazdani & Hall [44] suggests a relationship between medication use and falls. Thus, using medications with other factors will help improve the score and determine any possible correlations.

AHRQ provides tools such as assessing the safety culture in a hospital, leadership support development for a fall prevention program, and management of fall prevention practices [43]. The Medication Fall Risk tool is endorsed by the AHRQ, which determines medication-related risk factors in hospitalized patients. This tool is most beneficial in an acute care setting to prevent fall incidents. The Medication Fall Risk Assessment Tool considers the classification of medication that a patient is receiving and assigns a number on the scale. Based on total points, a patient is assigned to either of two high or low-risk groups. In combination with a nursing risk scale, this fall risk tool can be used to identify the relative risk of patients' falls. Thus, the individual healthcare staff can plan proper assistance based on the risk level [43].

The Institute for Healthcare Improvement recommends that healthcare be improved by considering population health, patient care experience, and the reduction of per capita healthcare costs. This can be called a triple aim of reforms and can be done by establishing proper communication protocols among all stakeholders [45]. Most of the population is aging, whereas fiscal and human healthcare resources are becoming increasingly scarce. Therefore, healthcare organizations need to improve the effectiveness of their communication standards with stakeholders to progress towards viable safety systems.

One of the significant issues regarding the testing of fall risk assessment tools is that most of these are tested in the same environment where they were designed and developed, mentioned in a study by Chapman et al. [46]. It is not possible to generalize the same research outcomes to all patients. Thus, this reduces the confidence level of researchers in terms of accuracy and sensitivity in the case of patient populations in a different environment. According to Chapman et al. [46], there is a difference in risk assessment tools and fall prevention strategies each organization uses. A comprehensive and evidence-based approach reviewed by the management committee of a healthcare organization is necessary to get effective results [45].

In the literature, it is common with all the tools that although they are accepted and widely used, they must reconsider and reevaluate the tools. The tools should be developed based on various patient populations and healthcare settings. For better understanding, the clinical assessment tools are explained in detail. These tools have gained a standard benchmark in determining risk scores and are used in various practice settings of hospitals. These tools are implemented in the US, translated into different languages, and used across the globe. The fall risk assessment tools most commonly used are:

1. Morse Fall Scale (MFS)
2. St. Thomas Risk Assessment Tool in Falling Elderly Inpatients (STRATIFY)
3. Johns Hopkins Fall Risk Assessment Tool (JHFRAT)
4. Stopping Elderly Accidents, Deaths, and Injuries (STEADI) Algorithm

The above tools are based on the questionnaire, and a patient is verbally consulted by asking these questions. The answers are recorded, and each question is assigned with points. Subsequently, the final score determines risk assessment, and a patient is then assigned to a group ranging from high to low. The popular tools used for clinical fall risk assessment are demonstrated with forms used for evaluation.

3.1 Morse Fall Scale (MFS)

The Morse Fall Scale, or MFS, was developed in 1985. It assesses six key factors: the history of falling, secondary diagnosis, ambulatory aid, IV/heparin lock, gait/transferring, and mental status. These key factors help determine the risk of falling for a patient, and evaluation is done on a scale of 0-30. It is a rapid and straightforward method [42]. Patients were classified as having a low (25), medium (26–50), or high (>51) risk of falling based on their overall scores. The Morse Fall Scale is demonstrated below:

Item	***Scale***	***Scoring***
1. History of falling; immediate or within 3 months	No 0 Yes 25	______
2. Secondary diagnosis	No 0 Yes 15	______
3. Ambulatory aid Bed rest/nurse assist Crutches/cane/walker Furniture	 0 15 30	______
4. IV/Heparin Lock	No 0 Yes 20	______
5. Gait/Transferring Normal/bedrest/immobile Weak Impaired	 0 10 20	______
6. Mental status Oriented to own ability Forgets limitations	 0 15	______

Figure 1. Morse Fall Scale [38]

3.2 St. Thomas Risk Assessment Tool in Falling Elderly Inpatients (STRATIFY)

The St. Thomas Risk Assessment Tool in Falling Elderly Inpatients or STRATIFY scale was developed in 1997. It mainly emphasizes behavioral attributes and comprises five different types of questionnaires. This tool focuses on the primary key factors: the recent history of falls, agitation, visually impaired, frequency of toileting, transfer, and mobility. Initially, the response is recorded in Yes or No answers and later converted to a score. Finally, a score is combined, and a score of 0 suggests low risk, 1 means moderate risk, and 2 or above is considered high risk [47].

Questions
1) Did the patient present to hospital with a fall or has he or she fallen on the ward since admission (recent history of fall)? 2) Is the patient agitated? 3) Is the patient visually impaired to the extent that everyday function is affected? 4) Is the patient in need of especially frequent toileting 5) Does the patient have a combined transfer and mobility score of 3 or 4 (calculate below)- Transfer score: Choose one of the following options which best describes the patients level of capability when transferring form a bed to a chair: 0 = unable 1 = needs major help 2 = needs minor help 3 = independent Mobility score: Choose one of the following options which best describes the patient's level of mobility: 0 = immobile 1 = independent with the aid of a wheelchair 2 = uses walking aid or help of one person 3 = independent Combined Score (transfer + mobility): _________ Total Score from questions 1-5: ______________ 0 = low risk | 1 = moderate risk | 2 or above = high risk

Figure 2. STRATIFY Fall Scale [44]

3.3 Johns Hopkins Fall Risk Assessment Tool (JHFRAT)

Johns Hopkins Medicine developed the Johns Hopkins model in 2005. It is an evidence-based initiative consisting of critical factors such as age, fall history, elimination/bowel/urine, medications, patient care equipment, mobility, and cognition. Each category has some points, and these points combined helps to determine the risk of falls. Patients were classified as having a low (0-6), medium (7-13), or high (14-35) risk of falling based on their overall scores (0-35). A score below 6 is a low fall risk, whereas more significant than 13 suggests high fall risk [48].

Criteria	Points
Age 60 - 69 years (1 point) 70 -79 years (2 points) greater than or equal to 80 years (3 points)	
Fall History One fall within 6 months before admission (5 points)	
Elimination, Bowel and Urine Incontinence (2 points) Urgency or frequency (2 points) Urgency/frequency and incontinence (4 points)	
Medications On 1 high fall risk drug (3 points) On 2 or more high fall risk drugs (5 points) Sedated procedure within past 24 hours (7 points)	
Patient Care Equipment One present (1 point) Two present (2 points) 3 or more present (3 points)	
Mobility (choose all that apply) Requires assistance or supervision for mobility, transfer, or ambulation (2 points) Unsteady gait (2 points) Visual or auditory impairment affecting mobility (2 points)	
Cognition (choose all that apply) Altered awareness of immediate physical environment (1 point) Impulsive (2 points) Lack of understanding of one's physical and cognitive limitations (4 points)	
Total Fall Risk Score	

Figure 3. Johns Hopkins Fall Risk Assessment Tool [45]

3.4 Stopping Elderly Accidents, Deaths, and Injuries (STEADI) Algorithm

The Stopping Elderly Accidents, Deaths, and Injuries STEADI Algorithm [49] is one of the most recent and advanced algorithms commonly used in healthcare. In 2003, CDC developed the STEADI Algorithm to screen and assess patients. The development of intervention strategies follows this gate fall risk factors with the help of clinical and managerial strategies. The American and British Geriatrics Societies Clinical Practice guidelines provide extensive support to this initiative. This algorithm uses a method of scoring based on a questionnaire to classify low, moderate, or high-risk patients. The algorithm is demonstrated below:

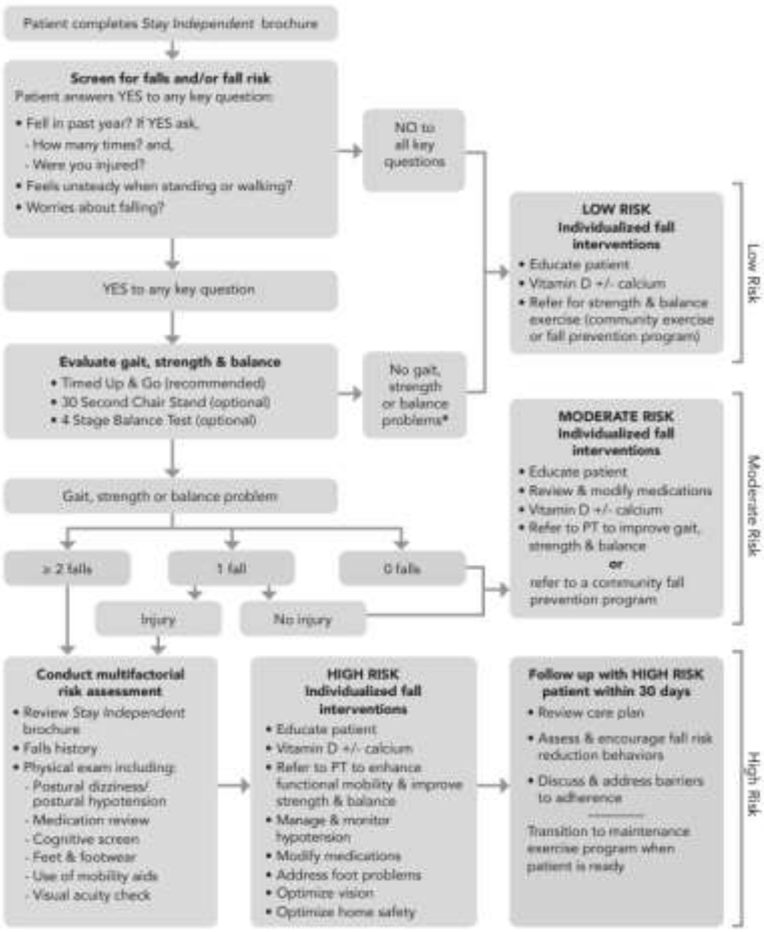

Figure 4. Stopping Elderly Accidents, Deaths, and Injuries (STEADI) Algorithm [46]

The tools discussed till now are specifically related to fall risk assessment. Other tools are used in hospital settings to predict health deterioration; for example, the Early Warning System (EWS) is the one. EWS are tools used by healthcare organizations to identify the early signs of a patient's clinical deterioration. This helps develop intervention strategies such as educating patients, increasing nursing attention, or activating the medical emergency team [50]. These EWS tools contain multiple physiological parameters such as temperature, heart rate, systolic blood pressure, oxygen saturation, urine output, level of consciousness, etc. A numeric value is assigned to each parameter, and a composite score is derived, which is used to identify a patient's health deterioration [49-50].

The first EWS developed by Morgan, Williams, and Wright in 1997 [52] consisted of five physiological parameters such as systolic blood pressure, temperature, heart rate, respiratory rate, and consciousness level. Each parameter was assigned with a score ranging from 0-3 to identify early signs of health deterioration [53]. For example, a score of 2 will be awarded to a heart rate between 115–129 bpm which indicates the need for initiating intervention. The EWS has been customized based on different parameters. The additional parameters like oxygen saturation and urine output are added to the original five physiological parameters in most EWS [53-54]. In a modified early warning system (MEWS), clinical signs of looking unwell, sweating, and pallor are included for observation but not scored [56]. The oxygen saturation parameter is added to the national early warning system (NEWS-2) to five basic parameters [57]. According to CDC, sepsis is a life-threatening emergency due to the body's response to an infection at an extreme level. The NEWS was revised to optimize the identification of sepsis and alternative oxygen targets for patients with underlying lung disease [58].

The EWS is used for providing early warnings to health providers in case of physiological and clinical health deterioration of a patient. For example, a prior indication of sepsis or delirium is an acute state of confusion that leads to a decline in mental functioning for a short period [59]. However, researchers suggest that EWS can provide early signs of adverse events such as in-hospital falls apart from these clinical health problems [60]. Our future work focuses on developing predictive modeling methods for fall prediction and comparing them based on performance metrics such as accuracy, specificity, sensitivity, etc. These methods will consist of significant parameters used to evaluate the fall risk. We will use machine learning algorithms to evaluate fall risk levels and classify patients in any one of the categories ranging from low to high fall risk. The proposed work can improve healthcare outcomes in small as well as large practice settings. Thus, finally improving the efficiency and reducing overall medical costs.

4 Research Gap and Objectives

The current fall risk assessment tools do not consider vital intrinsic and extrinsic factors. Although these tools offer an adequate degree of sensitivity and specificity, the fact that a high percentage of patients who fell were classified as low risk using the identified fall risk assessment instruments remains a source of worry [61]. The fall risk scales were created to identify patients at risk of falling, but the demographic and setting have been found to impact the results of these tests. These findings point to the difficulties in identifying at-risk individuals and key risk indicators applied to a wide range of acute care populations [61].

Limitations in fall risk assessment instruments and their incorrect application can result in the incorrect identification of a patient at risk of falling, as well as and non-implementation of fall prevention interventions and programs. This can provoke a dangerous diversion of attention and resources towards patients who would least benefit from preventative measures or ignore those who need them. As there is no gold standard for risk assessment, they cannot anticipate all inpatient falls, and therefore, while choosing a tool, hospitals must look at the prediction accuracy. Choosing the correct evaluation instrument can make a difference in whether a fall prevention program succeeds or fails.

Risk variables in assessment tools should be evaluated regularly to verify that they are still relevant to current therapies, such as medical interventions. Additionally, risk assessment tools like JHFRAT, MFS, and the STRATIFY do not account for all of the intrinsic and extrinsic fall risk factors that have been identified as contributing to inpatient falls.

Most of the fall risk assessment tools are developed by focusing more on the adult patient population above 65 years of age which ignores the assessment of the young population. Also, seasonality or month plays an important role in predicting falls. For example, if a patient is admitted during vacation, there can be a lack of human resources, which can hamper the patient-to-nurse ratio. Taking month into consideration will help management organize resources and maintain nurse-to-patient ratios. Finally, the current tools do not contain all the necessary factors, and each scale has only a few common elements. In such cases, there is a possibility of ignoring potential causes of falls. For example, MFS and STRATIFY do not assess medications or personal care equipment. The comparison of factors associated with each scale is given below.

Table 1. Comparison of factors

Factors	MFS	STRATIFY	JHFRAT
Age			✓
Fall History	✓	✓	✓
Frequency/Urgency of Bowel or Urine		✓	✓
Medications			✓
Patient Care Equipment			✓
Mobility	✓	✓	✓
Cognition			✓
Physically Disabled		✓	
Agitation		✓	
Secondary Diagnosis	✓		
IV/Heparin lock	✓		

The current tools consider the history of falls in terms of yes or no answers, but it fails to recognize if a patient was assisted or unassisted during past fall experiences. However, it is important to record if the person was assisted or using any assistive device during the past fall experience to understand the behavioral aspects. If the patient was unassisted by any means in past fall experience, then it is likely that nurse or caretaker must educate the patient on seeking assistance. The patient can seek assistance from staff or assistive devices while performing any activity that requires physical exertion.

The current assessment tools consider a patient's response, the only reliable source. But sometimes, it may not suffice the solid medical background. The wrong information by the patient can impact on fall risk assessment score. The patient usually fills the questionnaire which can be unreliable and impractical. This is because the response can potentially draw wrong medical conclusions, threatening a person's life and risk hospital recognition. As the questionnaire is paper-based, human error is possible because this score is calculated manually.

Some common features of fall risk assessment tools can be addressed in future work to avoid such adverse events.

Objective: Considering the gap between the ideal fall risk assessment tool and current tools, this research is meant to include variables not included in current tools. For example, it consists of the hospital department or location of the incident, presence of companion at the time of the incident, whether a restraint prescription was given. This study identifies the most effective fall prevention method by employing an accurate fall risk assessment tool that looks at the etiology of falls, intrinsic, extrinsic, and situational risk factors. It then matches the risks detected with suitable interventions.

The key focus area of this research is to build a predictive model for general-purpose risk assessment that can be utilized in the diverse practice setting in hospitals. As stated earlier, the current practices are mostly concerned with the older adult population (65 and above). Our work considers a person's age from 0 to 65 years and above to ensure the young population is not left out. The tool takes into account the weekday, shift, hospital department or location, environmental condition, severity, presence of companion, fall risk level, involvement of medication associated with fall risk, whether a fall prevention protocol was implemented type of injury incurred if any, and the reason for the incident type of hospital.

The analysis of patient falls will provide information to clinicians and guide them in developing interventions for patients. A solid initiative to prevent falls and a tool that offers precise risk scores are critical pieces for improving outcomes of falls. The general-purpose model comprised of diverse factors will help the healthcare system develop and target important fall areas. The present assessment tools align with analyzing causes of falls from historical data instead of present conditions. Our research work has the potential to motivate the development of a general-purpose, highly accurate, and practical tool that can successfully determine an individual’s risk score.

5 Data

The dataset used for analyzing falls consists of 1,070 in-hospital fall records between 2012 and 2017. The data was collected at a 497-bed institution known as Hospital Moinhos de Vento in South Brazil. The dataset is open source and can be accessed online [Dataset].

The dataset contains 18 variables corresponding to fall incidents.

1. Date of incident
2. Year
3. The birth decade of patient
4. The age range of patient
5. Sex of patient
6. Weekday of incident
7. Shift during which the incident occurred
8. Hospital department or location of the incident
9. Location or environment in which the incident occurred
10. Severity of incident
11. Presence of companion at the time of the incident
12. Fall risk level as measured by the Johns Hopkins Fall Risk Assessment Tool
13. Involvement of medication associated with fall risk
14. Whether a fall prevention protocol was implemented
15. Type of injury incurred if any
16. Reason for incident
17. Whether a restraint prescription was given
18. Whether a physical therapy prescription was given

5.1 Data Cleaning

The total data comprises 1,070 records that were reduced to 1069 after cleaning. After scanning all records, it was found that one record had missing values for "Whether a restraint prescription was given." This record was not considered to develop the final machine learning model as it will add very little value to the analysis.

5.2 Descriptive Analysis

The dataset consists of 18 variables; however, as mentioned before, not all variables are present for each year. Therefore, only 13 variables were used for analysis which is as follows:

1. The age range of patient
2. Sex of patient
3. Weekday of incident
4. Shift during which the incident occurred
5. Hospital department or location of the incident
6. Location or environment in which the incident occurred
7. Severity of incident
8. Presence of companion at the time of the incident
9. Fall risk level as measured by the Johns Hopkins Fall Risk Assessment Tool
10. Involvement of medication associated with fall risk
11. Whether a fall prevention protocol was implemented
12. Type of injury incurred if any
13. Reason for incident

The main objective of this project is to predict the risk of fall, so the “fall risk level as measured by the Johns Hopkins Fall Risk Assessment Tool” is considered as a predicted variable, and the remaining 12 variables are classified as predictor variables. The fall risk factors used in this study to predict the fall risk level vary from the factors used while calculating risk scores in JHFRAT. For example, in our study, we’re considering the hospital department as one of the risk factors which is not considered in JHFRAT. However, the dataset contains fall risk levels based on JHFRAT, and we’ll be using the same data for prediction.

The data is analyzed using descriptive statistics consisting of the measures of central tendency, i.e., mean and median, variability, absolute and relative distributions in Table 2 Characteristics of dataset.

Table 2 Characteristics of dataset

Total Sample Size (n) = 1070

Variable	N	% of Total
Weekday of incident		
Sunday	131	12.2%
Monday	133	12.4%
Tuesday	181	16.9%
Wednesday	160	15.0%
Thursday	165	15.4%
Friday	171	16.0%
Saturday	129	12.1%
Shift		
Afternoon	287	26.8%
Morning	374	35.0%
Night	409	38.2%
Hospital department or location of the incident		
A1	1	0.1%
Adult ACI	1	0.1%
Adult ICU	7	0.7%
Community	11	1.0%
Diagnostic support	82	7.7%
Dialysis	13	1.2%
Emergency department	121	11.3%
Inpatient units	784	73.3%
Ob&Gyn/Birth	17	1.6%
Oncology	12	1.1%
Operating room/recovery	18	1.7%
Pediatric/ neonatal ICU	3	0.3%
The age range of patient		
< 1	7	0.7%
1-12	34	3.2%
13-19	5	0.5%
20-29	37	3.5%
30-39	59	5.5%
40-49	73	6.8%
50-59	97	9.1%
60-69	194	18.1%
70-79	281	26.3%
80-89	230	21.5%
≥ 90	53	5.0%

Type of injury, if any		
Bruising	26	2.4%
Cut	65	6.1%
EDEMA	22	2.1%
Excoriation	122	11.4%
Fracture	19	1.8%
Head Trauma	5	0.5%
Hematoma	45	4.2%
No injury	764	71.4%
Spinal Cord injury	1	0.1%
Wound Dehiscence	1	0.1%
Location or environment in which the incident occurred		
Bathroom/shower	312	29.2%
Exam room	67	6.3%
Hallway	45	4.2%
Medical office	2	0.2%
Medication room	4	0.4%
Nursing station	1	0.1%
Operating room	2	0.2%
Others	15	1.4%
Outpatient adverse event	3	0.3%
Recovery room	5	0.5%
Room	581	54.3%
Surgical prep adverse event	3	0.3%
Surgical table	2	0.2%
Triage adverse event	1	0.1%
Vaccination room	1	0.1%
Waiting room	26	2.4%
Reason for incident		
Dizziness	1	0.1%
Equipment	9	0.8%
Human error	16	1.5%
Hypotension	99	9.3%
Loss of balance	324	30.3%
Mental confusion	138	12.9%
Muscle weakness	230	21.5%
Sedation	1	0.1%
Slip	189	17.7%
Syncope	1	0.1%
Trip	62	5.8%
Involvement of medication associated with fall risk		
No	412	38.5%
Yes	658	61.5%
Sex		
Female	572	53.5%

Male	497	46.5%
Presence of companion at the time of the incident		
No	390	36.5%
Yes	225	21.0%
Yes/Caregiver	16	1.5%
Yes/EQUIPE	1	0.1%
Yes/Family	296	27.7%
Yes/Nurse	117	10.9%
Yes/Physical therapist	18	1.7%
Yes/Physician	6	0.6%
Fall risk level		
High	633	59.2%
Low	50	4.7%
Moderate	386	36.1%
Whether a fall prevention protocol was implemented		
No	145	13.6%
Yes	925	86.4%
Severity of incident		
Adverse event	1045	97.7%
Sentinel event	2	0.2%
Serious adverse event	23	2.1%

1,070 falls were reported in the hospital. The number of falls during night (n = 409, 38.2%) were highest compared to afternoon (n = 287, 26.8%) and morning shifts (n = 374 , 35%). The afternoon shifts show the lowest number of falls. In terms of location, most falls occurred in the "room" (n = 581, 54.3%). A substantial proportion of falls (n = 312, 29.2%) were also seen in the bathroom/shower. The number of falls that occurred in the company of a companion (n = 679, 63.5 percent) was substantially higher than those that occurred without one. The companion was almost always a relative (n = 296, or 27.7%). A significant difference in the occurrence of falls was identified when comparing the occurrence of falls between high risk (n = 633, 59.2%) and moderate risk (n = 386, 36.1%) versus low risk (n = 50, 4.7%). It's worth noting that the gap between high and moderate risk was also large, with the proportion of fall occurrences among high-risk patients about double that of moderate-risk patients.

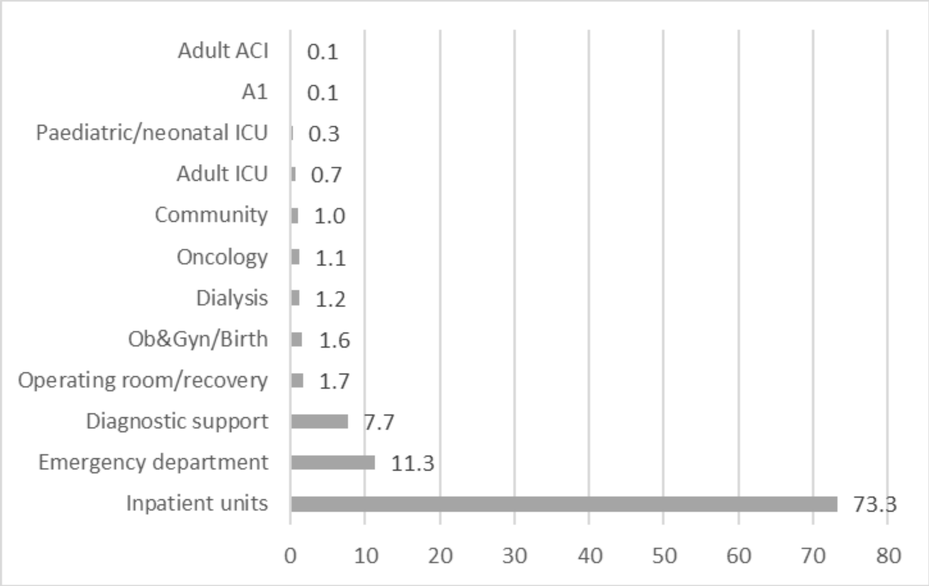

Figure 5. Distribution of falls according to location

Every patient at this hospital has their fall risk assessed regularly by a Registered Nurse. This information is stored in the medical record and is used to develop prevention programs. Figure 5. Distribution of falls according to location depicts the distribution of falls based on the incident's location. Inpatient unit falls (n = 784, or 73.3%) were substantially greater than in other areas. The primary causes of falls were loss of balance (n = 324, 30.3%) and motor deficit or muscle weakness (n = 23, 21.5%), both of which were substantially more common than other causes. In terms of severity, falls classified as adverse events were much more common (n = 1045, 97.7%) than serious or sentinel incidents (n = 25, 2.3%). Regarding fall-related injuries, the number of cases without injuries (n = 765, 71.4 %) was considerably greater than those with injuries (n = 306, 28.7%). The most prevalent form of injury was excoriations (n = 122, 311.4%).

Table 3. Total No. of falls based age group and reason of falls

Age group (years)	Reason (N)													
	Dizziness		Equipment		Human error		Hypotension		Loss of balance		Mental confusion		Muscle weakness	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
< 1	0	0.0%	0	0.0%	4	0.4%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
1-12	1	0.1%	0	0.0%	4	0.4%	0	0.0%	12	1.1%	1	0.1%	1	0.1%
13-19	0	0.0%	0	0.0%	0	0.0%	2	0.2%	1	0.1%	1	0.1%	1	0.1%
20-29	0	0.0%	0	0.0%	0	0.0%	10	0.9%	8	0.8%	3	0.3%	11	1.0%
30-39	0	0.0%	0	0.0%	0	0.0%	22	2.1%	13	1.2%	4	0.4%	12	1.1%
40-49	0	0.0%	1	0.1%	0	0.0%	13	1.2%	24	2.2%	4	0.4%	21	2.0%
50-59	0	0.0%	3	0.3%	2	0.2%	13	1.2%	22	2.1%	5	0.5%	30	2.8%
60-69	0	0.0%	1	0.1%	2	0.2%	15	1.4%	60	5.6%	32	3.0%	48	4.5%
70-79	0	0.0%	1	0.1%	3	0.3%	16	1.5%	90	8.4%	32	3.0%	61	5.7%
80-89	0	0.0%	2	0.2%	1	0.1%	8	0.8%	78	7.3%	43	4.0%	37	3.5%
≥ 90	0	0.0%	1	0.1%	0	0.0%	0	0.0%	16	1.5%	13	1.2%	8	0.8%
Total	1	0.1%	9	0.8%	16	1.5%	99	9.3%	324	30.3%	138	12.9%	230	21.5%

Table 3. (continued)

Age group (years)	Reason (N)									
	Sedation		Slip		Syncope		Trip		Total	
	N	%	N	%	N	%	N	%	N	%
< 1	0	0.0%	3	0.3%	0	0.0%	0	0.0%	7	0.7%
1-12	0	0.0%	6	0.6%	1	0.1%	8	0.8%	34	3.2%
13-19	0	0.0%	0	0.0%	0	0.0%	0	0.0%	5	0.5%
20-29	0	0.0%	2	0.2%	0	0.0%	3	0.3%	37	3.5%
30-39	0	0.0%	4	0.4%	0	0.0%	4	0.4%	59	5.5%
40-49	0	0.0%	8	0.8%	0	0.0%	2	0.2%	73	6.8%
50-59	0	0.0%	14	1.3%	0	0.0%	8	0.8%	97	9.1%
60-69	0	0.0%	27	2.5%	0	0.0%	9	0.8%	194	18.1%
70-79	1	0.1%	60	5.6%	0	0.0%	17	1.6%	281	26.3%
80-89	0	0.0%	52	4.9%	0	0.0%	9	0.8%	230	21.5%
≥ 90	0	0.0%	13	1.2%	0	0.0%	2	0.2%	53	5.0%
Total	1	0.1%	189	17.7%	1	0.1%	62	5.8%	1070	100%

Table 4. Total No. of falls based on injury type based on age group

Age group (years)	Reason (N) Bruising		Cut		EDEMA		Excoriation		Fracture		Head Trauma	
	N	%	n	%	n	%	n	%	n	%	n	%
< 1	0	0.0%	0	0.0%	0	0.0%	0	0.0%	1	14.3%	1	14.3%
1-12	1	2.9%	4	11.8%	4	11.8%	1	2.9%	0	0.0%	0	0.0%
13-19	1	20.0%	1	20.0%	0	0.0%	0	0.0%	0	0.0%	0	0.0%
20-29	2	5.4%	1	2.7%	0	0.0%	2	5.4%	0	0.0%	0	0.0%
30-39	3	5.1%	3	5.1%	2	3.4%	3	5.1%	0	0.0%	0	0.0%
40-49	2	2.7%	3	4.1%	2	2.7%	7	9.6%	1	1.4%	0	0.0%
50-59	0	0.0%	3	3.1%	5	5.2%	9	9.3%	1	1.0%	1	1.0%
60-69	6	3.1%	9	4.6%	3	1.6%	24	12.4%	3	1.6%	1	0.5%
70-79	7	2.5%	18	6.4%	4	1.4%	35	12.5%	7	2.5%	2	0.7%
80-89	4	1.7%	21	9.1%	2	0.9%	30	13.0%	3	1.3%	0	0.0%
≥ 90	0	0.0%	2	3.8%	0	0.0%	11	20.8%	3	5.7%	0	0.0%

Table 4. (continued)

Age group (years)	Reason (N) Hematoma		No injury		Spinal Cord injury		Wound Dehiscence		Total	
	n	%	n	%	n	%	n	%	n	%
< 1	0	0.0%	5	71.4%	0	0.0%	0	0.0%	7	0.7%
1-12	4	11.8%	20	58.8%	0	0.0%	0	0.0%	34	3.2%
13-19	0	0.0%	3	60.0%	0	0.0%	0	0.0%	5	0.5%
20-29	2	5.4%	30	81.1%	0	0.0%	0	0.0%	37	3.5%
30-39	1	1.7%	47	79.7%	0	0.0%	0	0.0%	59	5.5%
40-49	0	0.0%	58	79.5%	0	0.0%	0	0.0%	73	6.8%
50-59	1	1.0%	76	78.4%	0	0.0%	1	1.0%	97	9.1%
60-69	9	4.6%	139	71.7%	0	0.0%	0	0.0%	194	18.1%
70-79	11	3.9%	197	70.1%	0	0.0%	0	0.0%	281	26.3%
80-89	14	6.1%	155	67.4%	1	0.4%	0	0.0%	230	21.5%
≥ 90	3	5.7%	34	64.2%	0	0.0%	0	0.0%	53	5.0%

The number of falls was substantially greater in the 70–79 year old group (n = 281, 26.3%), the 80–89 year old group (n = 230, 21.5%), and the 60–69 year old group (n = 194, 18.1%). Falls were substantially linked with loss of balance (n = 90, 8.4%) and muscle weakness (n = 61, 5.7%) in the 70–79 year old group, and loss of balance (n = 78, 7.3%) and slips (n = 52, 4.9%) in the 80–89 year old group. In the 90-year and above old group, falls were mainly associated with loss of balance (n = 16, 1.5%) mental confusion (n = 13, 1.2%) and slips (n = 13, 1.2%), slips were also linked to falls. Falls were linked with human error (n = 4, 0.04%) and slips (n = 3, 0.3%) in the age group younger than one year; falls were associated with loss of balance (n = 12, 1.1%) and trip (n = 8, 0.08%) in the age group 1–12. Finally, hypotension was linked to falls in the 30–39 year old group (n = 22, 2.1%) and loss of balance to the 40–49 year old group (n = 24, 2.2%). Table 4. Total No. of falls based on injury type based on age groupdemonstrates that falls were linked with excoriation in the 70–79 year old group (n = 35, 12.5%), whereas excoriation (n = 13, 30%) and cuts (n = 21, 9.1%) were associated with falls in the 80–89 year old group.

5.3 Limitations

The data still lacks essential patient-related information like the type of medication. The name of medications may be helpful to determine future fall prevention research studies. The fall risk in the dataset is calculated by using JHFRAT and it contains "elimination/bowel/urine frequency" as part of its fall risk score calculation, but it is not part of the dataset. Also, there is no information on the method of score calculation for each record. The dataset is consolidated from one of the top-rated institutions by the Ministry of Health, Brazil [Dataset]. Therefore, the hospital provides top facilities like quality care, falls prevention programs, and good management across the organization. So the results may not be similar or applicable to other institutions with different features.

6 Methodology

The six-step approach has been adopted, as shown in Figure 6. Modeling Approachto develop a model to predict the injury level. Each step is explained in detail, along with the visual representation below. These steps have already been completed to define the problem statement, data understanding, data preparation, and exploratory data analysis.

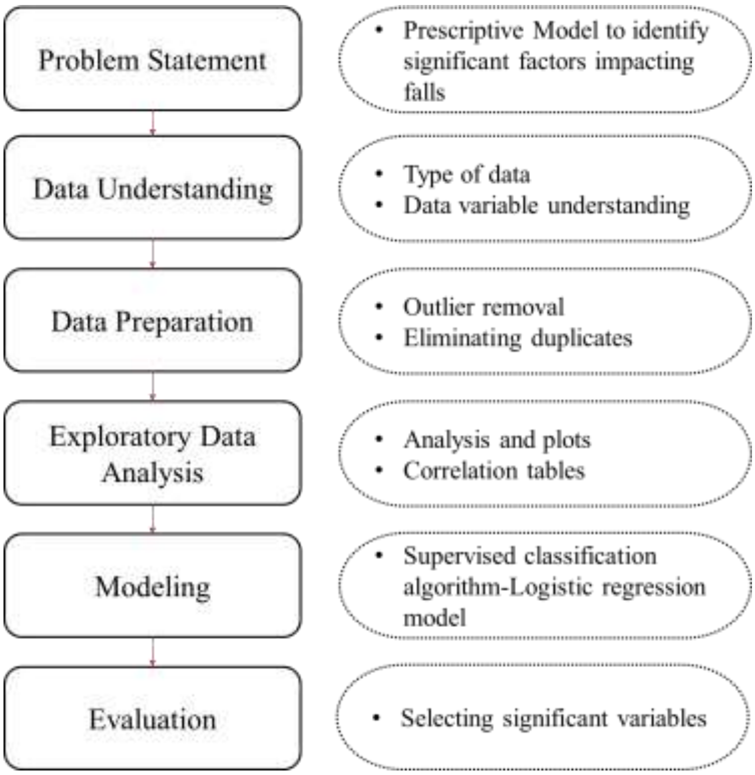

Figure 6. Modeling Approach

Step 1. Problem Statement: Defining a problem statement is essential for understanding specific objectives required to achieve by implementing the model.

Step 2. Data Understanding: Getting insight into data and dissecting information from it is crucial. This step is focused on cleaning and structuring the data and knowing the data type of each variable.

Step 3. Data Preparation: It is important to prepare data that is right for the analysis. This step involves initial cleaning by removing outliers or eliminating the duplicates.

Step 4. Exploratory Data Analysis (EDA): This step is significant in understanding the data by performing an initial investigation to discover patterns, spot abnormalities, and test hypotheses. It helps to obtain descriptive summary statistics and visual representation of the data.

Step 5. Modeling: Based on our goal, we have selected suitable modeling techniques (Support Vector Machine and Bootstrap Forest). The dataset contains qualitative variables, and we've developed and evaluated the performance of machine learning algorithms. (Section 6.1 has a detailed explanation of modeling techniques.)

Step 6. Evaluation: Later, the predictive performance of the two models is validated using error, the area under ROC, accuracy, sensitivity, specificity, positive predictive value, negative predictive value, odds ratio, etc.

This study aims to find the best suitable model for a relative risk of falls to varying patients' conditions and gain insight into the physiological nature of falls and their severity level. The preliminary results show that variation in the type of hospital, provision of assistance, and kind of hospital can result in varying levels of injury; peak time intervals like nighttime are a significant concern to maintain assistance standards for hospital management.

Additionally, the hospital department/location has been shown to impact the injury level substantially. These insights can form a solid foundation to build further models with additional factors, and it will help to understand the type of healthcare plan that a patient desires. The model outcomes will also support creating a self-care plan for the patient and a recommendation plan for the physician or hospital staff. This model can be made more dynamic in the future to support diverse practice settings by considering additional external and internal factors.

6.1 Modeling Techniques

Based on our goal, we have selected suitable modeling techniques. In this case, the machine learning algorithm is preferred. We used nominal logistic regression to evaluate the links between all predictors and fall risk levels, as shown in Table 5. Effect Likelihood Ratio Tests for all shifts Out of all the predictors, we can see that only three predictors (age range of patient, type of injury, and implementation of fall prevention protocol) are significant. The overall model is significant. However, the fall incidences took place during different time intervals, i.e., different shifts, therefore it does not provide a clear understanding of factors associated with fall risk levels. For example, the availability of resources such as nursing staff during different shifts plays a great role in assisting a patient. Therefore, we divided the dataset into three different sets based on shifts, i.e., morning shift, afternoon shift, and night shift as shown in Figure 7. Data flow diagram.

Table 5. Effect Likelihood Ratio Tests for all shifts

Source	DF	Prob>ChiSq
Weekday of incident	12	0.6711
Shift	4	0.5431
Hospital department or location of the incident	24	0.3573
The age range of patient	20	<.0001*
Type of injury incurred if any	18	0.8947
Presence of companion at the time of the incident	14	0.0606
Location or environment in which the incident occurred	30	0.0936
Reason for incident	20	0.0583
Whether a fall prevention protocol was implemented	2	<.0001*
Involvement of medication associated with fall risk	2	0.0008
Severity of incident	4	0.8977
Sex	2	0.3132

The previous studies show that researchers were able to use Support Vector Machine (SVM) and Bootstrap Forest (BF) methods to accurately predict unknown data to predict patients' fall risk [62-63]. Therefore, we trained the data and compared fall risk results using SVM and BF machine learning algorithms. The stepwise regression is used to understand the correlation of predictor factors to predicted variables in a step-by-step iterative manner, which includes the selection of independent variables to be utilized in the final model.

The dataset is split into three parts: training data, validation data, and testing data. The training data is some part of data used to fit the model, mostly it contributes to the majority part of the dataset [64]. While tuning model hyperparameters, validation data is used to offer evaluation of a model fit based on the training dataset that is unbiased [64]. The test data is a subset of data utilized to offer an unbiased assessment of a final model fit on the training dataset [64].

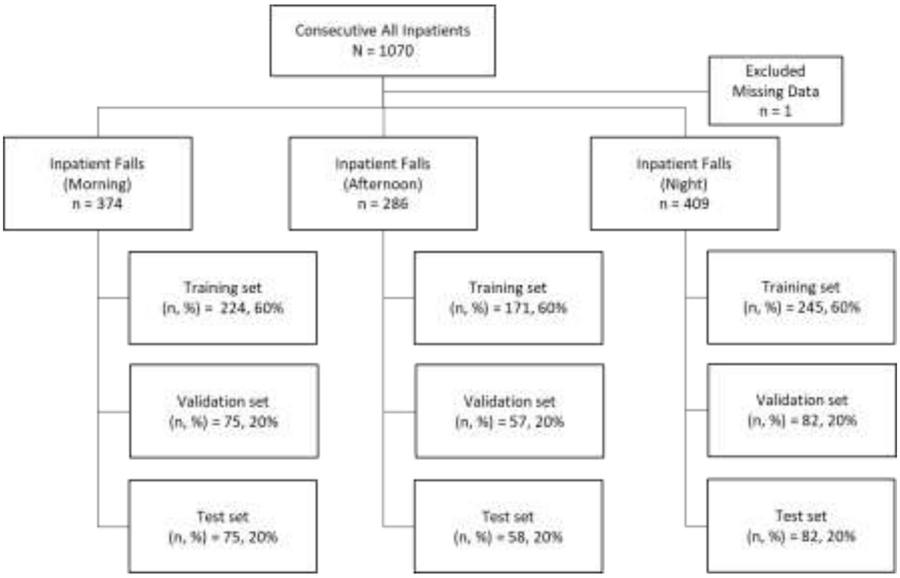

Figure 7. Data flow diagram

Error! Reference source not found. shows the dataset split into training, validation, and test based on commonly used ratios [65]:

Training set: 60%

Validation set: 20%

Test set: 20%

Total 1,070 all inpatient falls were recorded and 1069 records were chosen to do further statistical analysis. The night shift (n = 409) has highest incidences of fall following morning shift (n = 374) and afternoon shift (n = 286). Each shift is further divided into training, validation and test set. The morning shift dataset is comprised of training set (n, % = 224, 60%), validation set (n, % = 75, 20%), test set (n, % = 75, 20%). The afternoon shift dataset is comprised of training set (n, % = 171, 60%), validation set (n, % = 57, 20%), test set (n, % = 58, 20%). The night shift dataset is comprised of training set (n, % = 245, 60%), validation set (n, % = 82, 20%), test set (n, % = 82, 20%).

6.2 Predictor Variables

Stepwise regression is a technique for fitting multiple regression in which the selection of predictors is made automatically. It is recommended to use stepwise regression to select predictors without any prior knowledge of the data or the optimal model [66]. Each stage considers a variable for addition to or deletion from the set of variables based on a predetermined criterion. A forward, backward, or combination sequence of F-tests or t-tests is typically used for this [66]. We implemented a stepwise regression platform with combination sequence and p-value based halting criteria (p-values ≤ 0.25).

Further, based on the results of stepwise regression, we tried to fit the model using nominal logistic regression for each shift. Nominal logistic regression was used to investigate relationships between putative predictor factors and falls. Candidate predictor variables for nominal logistic regression models were identified as variables with individual p-values less than 0.05. The results of nominal logistic regression are discussed below.

Table 6. Effect Likelihood Ratio Tests (Morning Shift)

Source	DF	Prob>ChiSq
Weekday of incident	12	<.0001*
Hospital department or location of the incident	20	<.0001*
The age range of patient	20	<.0001*
Type of injury incurred if any	18	<.0001*
Presence of companion at the time of the incident	12	<.0001*
Location or environment in which the incident occurred	24	<.0001*
Reason for incident	14	<.0001*
Whether a fall prevention protocol was implemented	2	<.0001*
Involvement of medication associated with fall risk	2	<.0001*
Severity of incident	4	0.8484
Sex	2	0.9043

Table 7. Whole Model Test (Morning Shift)

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	142.02	130	284.04	<.0001*
Full	163.10			
Reduced	305.12			

The potential significant factors closely associated with fall risk level for the morning shift are represented in Table 6. Effect Likelihood Ratio Tests (Morning Shift). According to stepwise regression results, there were eleven predictor variables associated with falls in the morning shift. After running nominal logistic regression, we observed that nine predictors out of eleven are closely related to determine the fall risk level and have a p-value < .0001 based on effect likelihood ratio tests. These nine predictors are weekday, hospital department, age range, type of injury, presence of a companion, location of the incident, reason for the incident, fall prevention protocol, and medication involvement. It can be observed that the p-value of the overall model is <.0001 significant as well based on the whole model test shown in Table 7. Whole Model Test (Morning Shift).

Table 8. Effect Likelihood Ratio Tests (Afternoon Shift)

Source	DF	Prob>ChiSq
Weekday of incident	12	<.0001*
Hospital department or location of the incident	18	<.0001*
The age range of patient	20	<.0001*
Type of injury incurred if any	14	<.0001*
Presence of companion at the time of the incident	14	<.0001*
Location or environment in which the incident occurred	24	<.0001*
Reason for incident	14	<.0001*
Sex	2	<.0001*

Table 9. Whole Model Test (Afternoon Shift)

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	135.74	118	271.49	<.0001*
Full	119.65			
Reduced	255.40			

The potential significant factors closely associated with fall risk level for the afternoon shift are represented in Table 8. Effect Likelihood Ratio Tests (Afternoon Shift). According to stepwise regression results, there were eight predictor variables associated with falls in the afternoon shift. After running nominal logistic regression, we observed that all eight predictors are closely related to determining the fall risk level and have a p-value < .0001 based on effect likelihood ratio tests.

The eight predictors are weekday, hospital department, age range, type of injury, presence of a companion, location of the incident, reason for the incident, and sex. It can be observed that the p-value of the overall model is <.0001 significant as well based on a whole model test as shown in Table 9. Whole Model Test (Afternoon Shift).

Table 10. Effect Likelihood Ratio Tests (Night Shift)

Source	DF	Prob>ChiSq
Hospital department or location of the incident	14	0.0317*
The age range of patient	20	<.0001*
Type of injury incurred if any	14	0.9679
Presence of companion at the time of the incident	10	0.0354*
Reason for incident	18	0.1106

Table 11. Whole Model Test (Night Shift)

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	105.78	76	211.55	<.0001*
Full	205.46			
Reduced	311.24			

The potential significant factors closely associated with fall risk level for the night shift are represented in Table 10. Effect Likelihood Ratio Tests (Night Shift). Five predictor variables were associated with falls in the night shift as per stepwise regression results. After running nominal logistic regression, we observed that three predictors out of five are closely related to determining the fall risk level based on effect likelihood ratio tests. The three predictors are hospital department ($p = .0317$), age range ($p < .0001$), and presence of companion ($p < .0354$). It can be observed that the p-value of the overall model is <.0001 significant as well based on a whole model test as shown in Table 11. Whole Model Test (Night Shift). The significant predictor variables as a result of nominal logistic regression will be considered for running machine learning algorithms (SVM and BF), and the results of these models are discussed in Section 0. Results.

7 Results

In this section, the predictive performance of the two models (SVM and BF) is validated based on true positive value (TP), true negative value (TN), false-positive value (FP), false negative value (FN), area under ROC, precision, sensitivity, specificity, F1-score, accuracy, misclassification rate (MR), and false-positive rate (FPR).

Table 12. Significant Factors for Predictive Modeling

Significant Factors	Morning	Afternoon	Night
Weekday of incident	X	X	
Hospital department or location of the incident		X	X
The age range of patient	X	X	X
Type of injury incurred if any	X	X	
Presence of companion at the time of the incident		X	X
Location or environment in which the incident occurred	X	X	
Reason for incident	X	X	
Whether a fall prevention protocol was implemented			
Involvement of medication associated with fall risk	X		
Severity of incident			
Sex		X	

The performance parameters of the model are calculated based on the confusion matrix. It is a tabular representation of the prediction model's performance. Each entry in a confusion matrix represents the number of predictions made by the model in which the classes are positively or negatively classified [67]. We'll be using a multi-class confusion matrix as we have three fall risk levels - high, moderate, and low.

Table 13. Confusion matrix for fall risk

		Actual Falls	
		Positive	Negative
Predicted Falls	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

The metrics in the confusion matrix are explained below:

1. True Positive (TP): It's the number of times the classifier has successfully predicted the positive class as positive.
2. True Negative (TN): It's the number of times the classifier has successfully predicted the negative class as negative.
3. False Positive (FP): It's the number of times the classifier gets it wrong and forecasts the negative class as positive.
4. False Negative (FN): It's the number of times the classifier gets it wrong and forecasts the positive class as negative.

The confusion matrix provides a basic yet effective performance metric as the machine learning model's evaluation criteria. Following performance measures from the confusion matrix are used to evaluate the models:

1. Precision

It informs you what percentage of positive forecasts falls were truly positive. The value of precision is measured as below:

$$\text{Precision} = TP/(TP+FP)$$

2. Sensitivity

It informs you what percentage of all positive falls the classifier accurately predicted as positive. It is also called recall, probability of detection, or true positive rate (TPR). The value of sensitivity is measured as below:

$$\text{Sensitivity} = TP/(TP+FN)$$

3. Specificity

It informs you what percentage of all negative falls the classifier accurately predicted as negative. It is also called as true negative rate (TNR). The value of specificity is measured as below:

$$\text{Specificity} = TN/(TN+FP)$$

4. F1 – score

It's a single measure that combines precision and recall. It's the harmonic mean of precision and recall from a mathematical perspective. The value of specificity is measured as below:

$$\text{F1 – score} = 2*(\text{Precision}*\text{Recall}/\text{Precision} + \text{Recall}) = 2TP/(2TP+FP+FN)$$

A model with a precision of 1 and a recall of 1 would be ideal in an ideal world. That translates to an F1-score of 1, which indicates 100 percent accuracy, which is rarely the case with machine learning models.

5. Accuracy

It shows you the model's overall accuracy or the percentage of total samples correctly identified by the classifier. The higher the accuracy value, the better the model is [67]. The value of accuracy is measured as below:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

6. Misclassification Rate (MR)

Also called classification rate, it is the percentage of the wrong guesses. The lower the accuracy value, the better the model is. The value of misclassification rate is measured as below:

Misclassification Rate = (FP + FN) / (TP + TN + FP + FN) or (1 – Accuracy)

7. False Positive Rate (FPR)

The ratio between the number of negative events incorrectly classified as positive (false positives) and the total number of true negative events is used to compute the false positive rate (regardless of classification). It is also known as the false-positive ratio. The value of FPR is measured as below:

False Positive Rate = FP / (FP + TN)

7.1 Predictive performance comparison

In this section, we'll evaluate the performance of SVM and BF with respective shifts and severity. Our study evaluated performance for the severity of falls that come under high and moderate categories. Table 14. Model performance for testing data (low severity)shows model performance evaluation for fall risk with a low severity group of patients, which is not considered part of our study.

Table 14. Model performance for testing data (low severity)

Shift	Morning		Afternoon		Night	
Parameters	SVM	BF	SVM	BF	SVM	BF
TP	0	0	0	0	0	0
TN	69	69	52	52	79	79
FP	3	3	6	6	3	3
FN	3	3	0	0	0	0
Precision	N/A	N/A	N/A	N/A	N/A	N/A
Sensitivity	N/A	N/A	N/A	N/A	N/A	N/A
Specificity	N/A	N/A	N/A	N/A	N/A	N/A
F1 score	N/A	N/A	N/A	N/A	N/A	N/A
Accuracy	N/A	N/A	N/A	N/A	N/A	N/A

MR	N/A	N/A	N/A	N/A	N/A	N/A
FPR	N/A	N/A	N/A	N/A	N/A	N/A

The main reason is that we found for testing data, the patients that the classifier has successfully predicted as the positive class as positive resulted in zeroes for all three shifts considering both models SVM and BF. Similarly, false negatives are zeroes for afternoon and night shifts for SVM/BF. This further tends to have F1-score and recall as 0. We did not include it as part of our results to avoid misinterpretation of data. This can impact the validity of results, hindering the correct prediction of a low severity group of patients.

a. Predictive performance comparison – Morning Shift

Table 15. Confusion matrix for test data – SVM (Morning)Table 16. Confusion matrix for test data – BF (Morning)represents confusion matrix for SVM and BF for the morning shift.

Considering the test data, SVM (accuracy, % = 75) has better accuracy compared to BF (accuracy, % = 69) with misclassification rate of 25% and 31% for high severity of falls. SVM (accuracy, % = 69) has better accuracy compared to BF (accuracy, % = 61) with misclassification rate of 31% and 39% for moderate severity of falls. As mentioned earlier low severity of falls are not considered for performance evaluation. Figure 8. ROC for SVM and BFshows ROC for SVM and BF for all three shifts. For morning shift and high severity rate, SVM (AUC, % = 76) and BF (AUC, % = 76) have similar receiver operating characteristics. For morning shift and moderate severity rate, BF (AUC, % = 72) has more area compared to SVM (AUC, % = 71).

Table 17. Performance evaluation (Morning Shift)represents performance measures of SVM and BF models for predicting falls during the morning shift. The performance is evaluated separately for each severity of falls measured in three categories – high, moderate, and low.

Table 15. Confusion matrix for test data – SVM (Morning)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate

High	35	0	7
Low	1	0	2
Moderate	11	3	16

Table 16. Confusion matrix for test data – BF (Morning)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	33	0	9
Low	1	0	2
Moderate	13	0	17

Considering the test data, SVM (accuracy, % = 75) has better accuracy compared to BF (accuracy, % = 69) with misclassification rate of 25% and 31% for high severity of falls. SVM (accuracy, % = 69) has better accuracy compared to BF (accuracy, % = 61) with misclassification rate of 31% and 39% for moderate severity of falls. As mentioned earlier low severity of falls are not considered for performance evaluation. Figure 8. ROC for SVM and BFshows ROC for SVM and BF for all three shifts. For morning shift and high severity rate, SVM (AUC, % = 76) and BF (AUC, % = 76) have similar receiver operating characteristics. For morning shift and moderate severity rate, BF (AUC, % = 72) has more area compared to SVM (AUC, % = 71).

Table 17. Performance evaluation (Morning Shift)

Shift	Parameters	Support Vector Machine			Bootstrap Forest		
		High	Moderate	Low	High	Moderate	Low
Training	TP	124	64	10	125	61	1
	TN	74	134	214	69	128	214
	FP	4	22	0	3	25	9
	FN	22	4	0	27	10	0
	Precision	0.63	0.74	N/A	0.98	0.71	N/A
	Sensitivity	0.85	0.94	N/A	0.82	0.86	N/A
	Specificity	0.95	0.86	N/A	0.96	0.84	N/A
	F1 score	0.91	0.83	N/A	0.89	0.78	N/A
	Accuracy	0.88	0.88	N/A	0.87	0.84	N/A
	MR	0.12	0.12	N/A	0.13	0.16	N/A
	FPR	0.05	0.14	N/A	0.04	0.16	N/A
Validation	TP	41	13	1	38	10	0
	TN	17	42	71	12	39	72

	FP	6	12	2	9	15	3
	FN	11	8	1	16	11	0
	Precision	0.87	0.52	N/A	0.81	0.40	N/A
	Sensitivity	0.79	0.62	N/A	0.70	0.48	N/A
	Specificity	0.74	0.78	N/A	0.57	0.72	N/A
	F1 score	0.83	0.57	N/A	0.75	0.43	N/A
	Accuracy	0.77	0.73	N/A	0.67	0.65	N/A
	MR	0.23	0.27	N/A	0.33	0.35	N/A
	FPR	0.26	0.22	N/A	0.43	0.28	N/A
Test	TP	35	16	0	33	17	0
	TN	21	36	69	19	20	69
	FP	7	14	3	9	13	3
	FN	12	9	3	14	11	3
	Precision	0.83	0.53	N/A	0.79	0.57	N/A
	Sensitivity	0.74	0.64	N/A	0.70	0.61	N/A
	Specificity	0.75	0.72	N/A	0.68	0.61	N/A
	F1 score	0.79	0.58	N/A	0.74	0.59	N/A
	Accuracy	0.75	0.69	N/A	0.69	0.61	N/A
	MR	0.25	0.31	N/A	0.31	0.39	N/A
	FPR	0.25	0.28	N/A	0.32	0.39	N/A

b. Predictive performance comparison – Afternoon Shift

Table 18. Confusion matrix for test data – SVM (Afternoon)Table 19. Confusion matrix for test data – BF (Afternoon) represents confusion matrix for SVM and BF for the afternoon shift. Table 20. Performance evaluation (Afternoon Shift)

Table 18. Confusion matrix for test data – SVM (Afternoon)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	19	0	13
Low	1	0	5
Moderate	9	0	11

Table 19. Confusion matrix for test data – BF (Afternoon)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	20	0	12
Low	0	0	6
Moderate	8	0	12

Table 20. Performance evaluation (Afternoon Shift) represents performance measures of SVM and BF models for predicting falls for the afternoon shift.

Considering the test data, BF (accuracy, % = 66) has better accuracy compared to SVM (accuracy, % = 60) with misclassification rate of 34% and 40% for high severity of falls. BF (accuracy, % = 55) has better accuracy compared to SVM (accuracy, % = 53) with misclassification rate of 45% and 47% for moderate severity of falls. As mentioned earlier low severity of falls are not considered for performance evaluation. For afternoon shift and high severity rate, BF (AUC, % = 72) has more area compared to SVM (AUC, % = 65). For afternoon shift and moderate severity rate, BF (AUC, % = 53) has more area compared to SVM (AUC, % = 51).

Table 18. Confusion matrix for test data – SVM (Afternoon)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	19	0	13
Low	1	0	5
Moderate	9	0	11

Table 19. Confusion matrix for test data – BF (Afternoon)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	20	0	12
Low	0	0	6
Moderate	8	0	12

Table 20. Performance evaluation (Afternoon Shift)

Shift	Parameters	Support Vector Machine			Bootstrap Forest		
		High	Moderate	Low	High	Moderate	Low
Training	TP	78	47	7	84	61	6
	TN	57	89	157	71	93	158
	FP	9	24	6	3	10	7
	FN	27	11	1	13	7	0
	Precision	0.90	0.66	N/A	0.97	0.86	N/A
	Sensitivity	0.74	0.81	N/A	0.87	0.90	N/A
	Specificity	0.86	0.79	N/A	0.96	0.90	N/A
	F1 score	0.81	0.73	N/A	0.91	0.88	N/A
	Accuracy	0.79	0.80	N/A	0.91	0.90	N/A
	MR	0.21	0.20	N/A	0.09	0.10	N/A
	FPR	0.14	0.21	N/A	0.04	0.10	N/A
Validation	TP	28	6	0	24	7	0
	TN	9	28	54	9	25	54
	FP	11	9	3	15	8	3
	FN	9	14	0	9	17	0
	Precision	0.72	0.40	N/A	0.62	0.47	N/A
	Sensitivity	0.76	0.30	N/A	0.73	0.29	N/A
	Specificity	0.45	0.76	N/A	0.38	0.76	N/A
	F1 score	0.74	0.34	N/A	0.67	0.36	N/A
	Accuracy	0.65	0.60	N/A	0.58	0.56	N/A
	MR	0.35	0.40	N/A	0.42	0.44	N/A
	FPR	0.55	0.24	N/A	0.63	0.24	N/A
Test	TP	19	11	0	20	12	0
	TN	16	20	52	18	20	52
	FP	13	9	6	12	8	6
	FN	10	18	0	8	18	0
	Precision	0.59	0.55	N/A	0.63	0.60	N/A
	Sensitivity	0.66	0.38	N/A	0.71	0.40	N/A
	Specificity	0.55	0.69	N/A	0.60	0.71	N/A
	F1 score	0.62	0.45	N/A	0.67	0.48	N/A
	Accuracy	0.60	0.53	N/A	0.66	0.55	N/A
	MR	0.40	0.47	N/A	0.34	0.45	N/A
	FPR	0.45	0.31	N/A	0.40	0.29	N/A

c. Predictive performance comparison – Night Shift

Table 21. Confusion matrix for test data – SVM (Night)Table 22. Confusion matrix for test data – BF (Night) represents confusion matrix for SVM and BF for night shift. Table 23. Performance evaluation (Night Shift)represents the performance of SVM and BF models for predicting falls for the night shift.

Considering the test data, SVM (accuracy, % = 76) and BF (accuracy, % = 76) has same accuracy with misclassification rate of 24% for high severity of falls. SVM (accuracy, % = 74) and BF (accuracy, % = 74) has same accuracy with misclassification rate of 24% for moderate severity of falls. As mentioned earlier low severity of falls are not considered for performance evaluation. For night shift and high severity rate, BF (AUC, % = 79) has more area compared to SVM (AUC, % = 59). For night shift and moderate severity rate, BF (AUC, % = 76) has more area compared to SVM (AUC, % = 61).

Table 21. Confusion matrix for test data – SVM (Night)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	53	0	5
Low	1	0	2
Moderate	14	0	7

Table 22. Confusion matrix for test data – BF (Night)

Actual	Predicted Count		
Fall risk level	High	Low	Moderate
High	53	0	5
Low	1	0	2
Moderate	14	0	7

Table 23. Performance evaluation (Night Shift)

Shift	Parameters	Support Vector Machine			Bootstrap Forest		
		High	Moderate	Low	High	Moderate	Low
Training	TP	144	45	1	144	41	0
	TN	48	147	240	43	147	240
	FP	12	39	4	12	43	5
	FN	41	14	0	46	14	0
	Precision	0.92	0.54	N/A	0.92	0.49	N/A
	Sensitivity	0.78	0.76	N/A	0.76	0.75	N/A
	Specificity	0.80	0.79	N/A	0.78	0.77	N/A
	F1 score	0.84	0.63	N/A	0.83	0.59	N/A
	Accuracy	0.78	0.78	N/A	0.76	0.77	N/A
	MR	0.22	0.22	N/A	0.24	0.23	N/A
	FPR	0.20	0.21	N/A	0.22	0.23	N/A
Validation	TP	41	17	0	42	17	0
	TN	21	42	77	20	43	78
	FP	3	17	4	2	17	4
	FN	17	6	1	18	5	0
	Precision	0.93	0.50	N/A	0.95	0.50	N/A
	Sensitivity	0.71	0.74	N/A	0.70	0.77	N/A
	Specificity	0.88	0.71	N/A	0.91	0.72	N/A
	F1 score	0.80	0.60	N/A	0.81	0.61	N/A
	Accuracy	0.76	0.72	N/A	0.76	0.73	N/A
	MR	0.24	0.28	N/A	0.24	0.27	N/A
	FPR	0.13	0.29	N/A	0.09	0.28	N/A
Test	TP	53	7	0	53	7	0
	TN	9	54	79	9	54	79
	FP	5	14	3	5	14	3
	FN	15	7	0	15	7	0
	Precision	0.91	0.33	N/A	0.91	0.33	N/A
	Sensitivity	0.78	0.50	N/A	0.78	0.50	N/A
	Specificity	0.64	0.79	N/A	0.64	0.79	N/A
	F1 score	0.84	0.40	N/A	0.84	0.40	N/A
	Accuracy	0.76	0.74	N/A	0.76	0.74	N/A
	MR	0.24	0.26	N/A	0.24	0.26	N/A
	FPR	0.36	0.21	N/A	0.36	0.21	N/A

7.2 Receiver Operator Characteristic (ROC) curve

The Receiver Operator Characteristic (ROC) curve or area under the curve (AUC) is a binary classification issue evaluation metric. It's a probability curve that displays the TPR against the FPR at different threshold levels, thereby separating the 'signal' from the 'noise'. A greater X-axis value in a ROC curve suggests a higher number of False positives than True negatives. While a higher Y-axis value implies a greater number of True positives than False negatives, a lower Y-axis value suggests fewer True positives. As a result, the threshold is determined by balancing False positives and False negatives. Figure 8. ROC for SVM and BFrepresents visual representation for ROC while 7.1 includes AUC results for each model for all three shifts.

The model parameters are trained and evaluated by minimizing the loss. Loss is a function representing the number of errors predicted by the model. The evaluation of the models is done for different so-called "hyper-parameters" values. These values include nodes and layers based on the receiver operating characteristic (ROC) curves. The models are prone to errors and can make false positive and negative predictions. Additionally, at the expense of the other models, it is possible to tweak a single model to minimize one type of error. The area under the ROC curve represents these types of multiple-choice trade-offs.

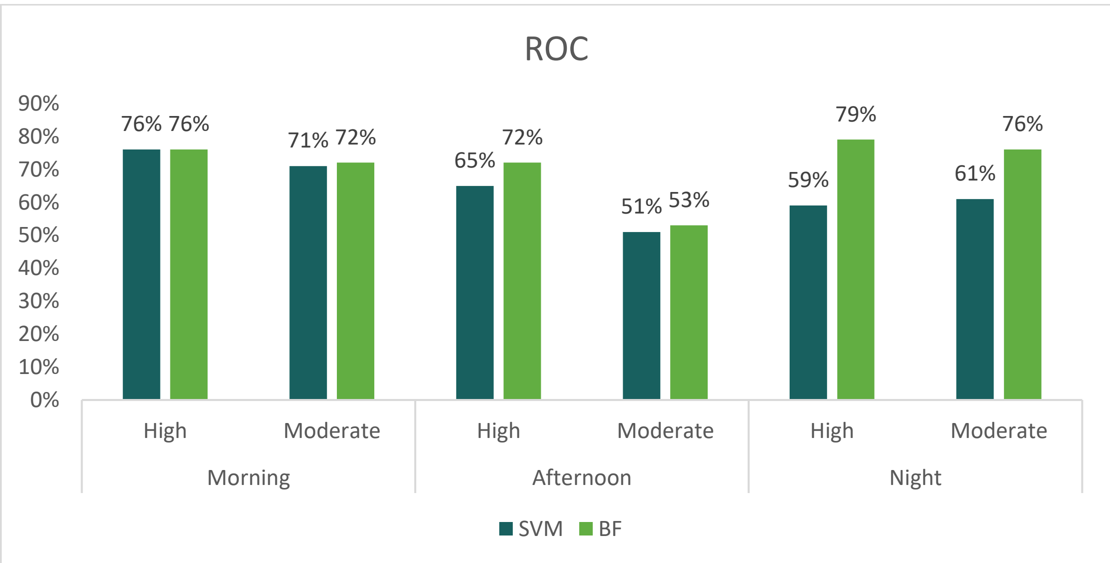

Figure 8. ROC for SVM and BF

8 Discussion

This study developed and compared fall risk prediction machine learning models for use in general-purpose healthcare settings using data collected from a large hospital in South Brazil [Dataset]. This dataset contains 6yrs retrospective data, and it has been previously used to analyze significant factors responsible for determining fall risk and develop prediction tools. Our models (SVM and BF) provide comparable accuracy to conventional models such as JHFRAT, STRATIFY, or MFS in the assessment of fall risk. We observed the following results in our study that will help to develop mitigation strategies for reducing in-patient falls:

a. The shifts (morning, afternoon, or night) influences the selection of predictors:

Predictors such as weekday, patient age, injury type, location of incidence, the reason for fall, and medication have a close association with fall risk level during the morning shift. In the case of the afternoon shift, the predictors such as weekday, hospital department, age of the patient, injury type, presence of a companion, location of incidence, reason for fall, and severity of fall have a close association with the fall risk level. During the night shift, predictors such as hospital department, age, and companion play a vital role in predicting fall risk levels.

b. The performance of models vary from shift to shift:

Figure 9. Overall Accuracy of SVM and BFFigure 9. Overall Accuracy of SVM and BFshows the overall accuracy of both models, SVM, and BF, considering high and moderate severity levels for each shift. It can be observed that SVM (accuracy, % = 68) outperforms BF (accuracy, % = 67) for morning shift, BF (accuracy, % = 55) outperforms SVM (accuracy, % = 52) for afternoon shift whereas BF (accuracy, % = 73) and SVM (accuracy, % = 73) have same accuracy rate during night shift. This shows that the performance of SVM and BF is different based on shifts. Also, the misclassification rate varies based on the level of fall severity.

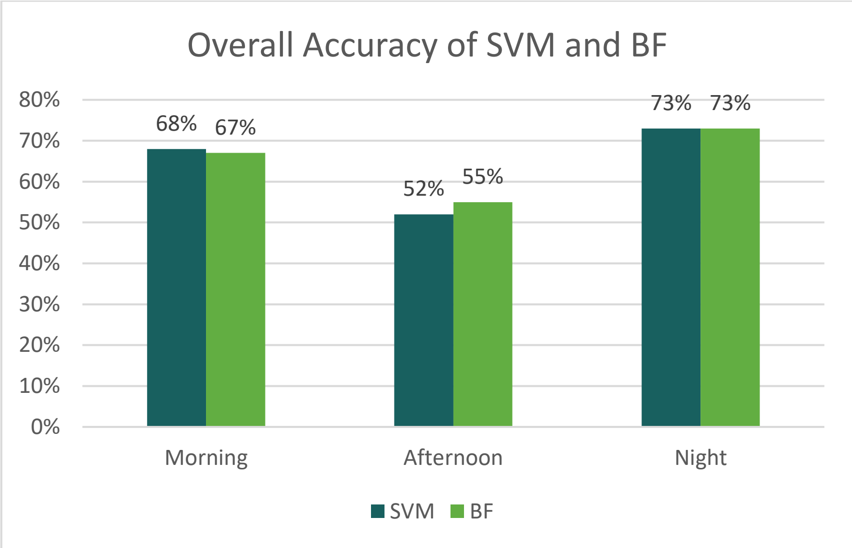

Figure 9. Overall Accuracy of SVM and BF

Figure 10. Overall Misclassification Rate of SVM and BFFigure 10. Overall Misclassification Rate of SVM and BFFigure 10. Overall Misclassification Rate of SVM and BFshows the overall misclassification rate of both models SVM and BF, considering high and moderate severity levels for each shift. For morning shift and high severity level, SVM (MR, % = 25) has lower misclassification rate compared to BF (MR, % = 31). For morning shift and moderate severity level, SVM (MR, % = 31) has lower misclassification rate compared to BF (MR, % = 39). For morning shift and moderate severity level, SVM (MR, % = 31) has lower misclassification rate compared to BF (MR, % = 39).

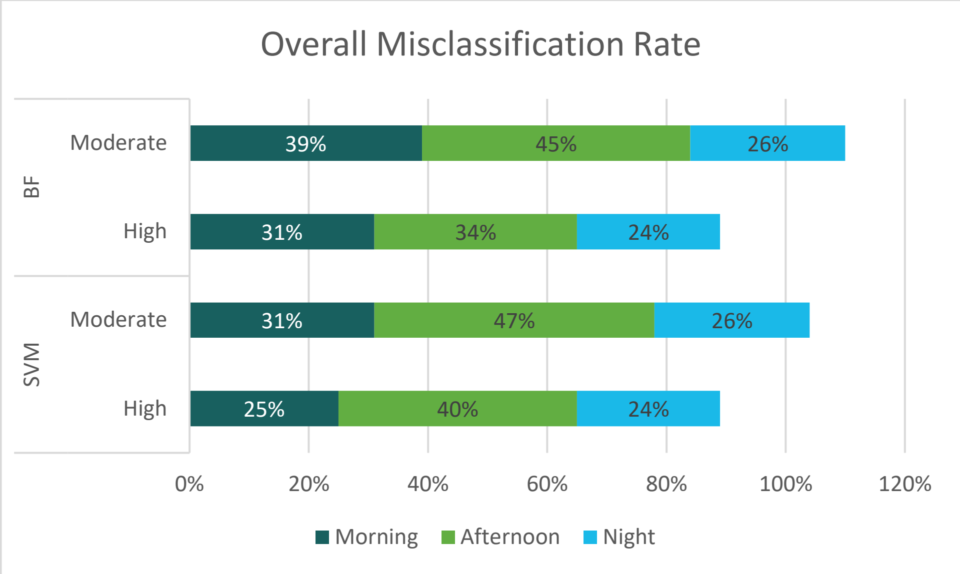

Figure 10. Overall Misclassification Rate of SVM and BF

For afternoon shift and high severity level, BF (MR, % = 34) has lower misclassification rate compared to SVM (MR, % = 40). For afternoon shift and moderate severity level, BF (MR, % = 45) has lower misclassification rate compared to SVM (MR, % = 47). For night shift and high severity level, BF (MR, % = 24) and SVM (MR, % = 24) have same misclassification rate. Similarly, for night shift and moderate severity level, BF (MR, % = 26) and SVM (MR, % = 26) have same misclassification rate

8.1 Contribution of study

The findings of this literature review show a link between falls and the relevant extrinsic and intrinsic factors that increase the risk of falling. The findings of recent literature analysis of risk variables offer clinicians information on some of the most important criteria to consider when assessing fall risk and fall prevention measures. In clinical practice, identifying evidence-based predictive fall risk variables helps identify relevant risk factor commonalities among hospitalized inpatients. These serious problems necessitate developing and implementing a new evidence-based fall risk predictor tool.

Our study contributes significantly to research in healthcare and industrial engineering. It helps to understand new dimensions on shift-wise analysis and standardize fall risk assessment tools. The relatively high sample size, analytical technique, and systematic development of the instrument are strengths of this work. Most crucially, the study generated absolute risk prediction ratings for people on a categorical scale. Our fall risk prediction models based on machine learning provide comparable accuracy to conventional models in assessing fall risk.

We used predictive modeling to predict the risk of falls in hospitalized patients, using statistical analysis to predict outcomes [69]. When it comes to prediction, the event is yet to occur or is likely to happen in the future. At the same time, the predictive modeling technique can be applied to unknown events of any type, regardless of when it has taken place. For example, in the case of fall risk assessment, the predictive model can detect injury levels even after the patient has sustained a fall in the past [70]. We used SVM and BF machine learning models using deep learning, composed of multiple layers to process and learn data with the abstraction of multiple levels [73].

SVM and BF models are statistically robust because the data and quality of the model determine the feature computations' complexity instead of the operator’s preconception. Additionally, no prior knowledge or certification is required to build a predictive model compared with other traditional machine learning algorithms. The iterative feature of machine learning is crucial because models can evolve independently as they are exposed to fresh data. They use past computations to provide consistent, repeatable judgments and outcomes. The SVM and BF models provide comparable accuracy to conventional models in assessing fall risk.

9 Limitations

One of the study's limitations is that the data comes from a single source and includes a fewer number of records. Therefore, regarding any predicative fall hazards, the chance of mistakes, missing information, and undisclosed variables cannot be ruled out. This research is intended to develop machine learning models to predict fall risk by considering relevant intrinsic and extrinsic factors. However, single-source data limits the possibility of developing a generalized fall risk assessment based on machine learning techniques as it cannot be applied to different healthcare settings.

All of the studies used a retrospective design, and as the data was obtained for clinical recording purposes rather than research, prospective validation of fall risk factors is limited. The external validity of the included studies cannot be determined because it's hard to assume that the details of the documented fall incidences were reported consistently. The demographic data was not available for all of the studies in the evaluation. Therefore, we have not considered percentages adjusted for demographic variations, limiting the extent to which conclusions could be applied to different ethnicities and age groups.

Although the dataset includes whether a patient was on medication, it lacks information about the type of medications. This could jeopardize the study's external validity, as older patients are more likely to have chronic co-morbidities, which predispose them to impairments and higher fall risk. There is the possibility that differences may have influenced the reliability analysis in patient knowledge amongst different nurses. For example, the nurse who had direct patient care responsibilities may have better information than other nurses who did not directly contact a patient. Also, it cannot be overlooked that handwritten or electronic data collecting might be vulnerable to discrepancies in clinical documentation.

10 Future Work

Our study provides the foundation for predictive modeling for future research to identify and evaluate predicting fall risk factors. Future studies should adhere to the stringent procedures required for this goal, considering methodological concerns. The predictive model should be updated frequently to the most recent predictors.

Considering a patient's health, it's difficult to tell if a patient's fall risk and incidence are caused by a drug's therapeutic action or by their underlying co-morbidities. Future work should focus on the type of drugs used and underlying co-morbidities if any. Additionally, future work should also try to optimize the model statistically. To improve the precision and calculation of risk severity and information translating risk factors into clinical settings, further epidemiological research is recommended. The results vary based on shifts, and thus in the future, it'll be better to combine both SVM and BF, allowing auto-select the best model based on different shifts.

SVM and BF showed similar characteristics for the low severity group. As discussed earlier, we did not consider the true positives as they are zeroes for all three shifts and false negatives are 0 for the afternoon and night shifts. Therefore we need additional research on low severity group of patients. Lastly, it is critical to emphasize that all institutional development efforts, such as the deployment of incident reporting systems, must strive to generate learning and discover solutions capable of preventing major events from occurring in the first place. Also, the frontline workers are responsible for continual improvement since they are familiar with patient care processes, so they require education and training at all levels.

11 Conclusions

The facts are unmistakable: falls do happen. Patients in hospitals are in danger of falling and being injured due to the fall. These falls have a significant impact on the patient and increase the length of stay in the hospital and the expense of care. Every organization should have a mechanism to assess each inpatient's risk of falling. This procedure starts with a screening that predicts and distinguishes those at risk of falling so that treatments can be used to reduce or eliminate the risk.

Falls are a major medical, legal, and economic concern for hospitals. Patients' safety is jeopardized by falls and falls with injuries. We identified that based on shifts, predictors could vary significantly. In conclusion, we developed new predictive models based on the machine learning algorithm, SVM, and BF. These tools can be used in healthcare settings to develop a standardized tool for predicting fall risk. We identified intrinsic/extrinsic factors that are closely associated with fall risk. Finally, we compared the performance of models based on metrics derived from the confusion matrix.

Because patient care methods are constantly changing, there is no single clear solution to the issues faced by patient falls in hospitals. Therefore, the first step is to develop a comprehensive fall risk assessment instrument that addresses the most recent predictive indicators while maintaining an acceptable degree of sensitivity and specificity.

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