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Utilizing machine learning to identify fall predictors in India's aging population: findings from the LASI

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Abstract

Background Depression has a detrimental effect on an individual's mental and musculoskeletal strength multiplying the risk of fall incidents. The current study aims to investigate the association between depression and falls in older adults using machine learning (ML) approach and identify its various predictors.

Methods Data for the study was derived from the Longitudinal Ageing Study in India, (LASI) conducted in 2017–18 for people aged 45-years and above. The study was carried out on 44,066 individuals. Depression was measured using the CIDI-SF scale. Bivariate cross-tabulations were used to study the prevalence of falls. And its association with depression and other independent factors were assessed using the novel ML, the Conditional inference trees (CIT) method.

Results Around 10.8 percent of older adults had fall incidents. CIT model predicted region to be a significant predisposing factor for an older adult to experience falls. Multimorbidity, depression, sleep problems, and gender were other prominent factors. The model predicted that, among depressed older adults, falls incidents were around 80 percent higher than non-depressed.

Conclusions An association between falls and depression was observed. Depressive symptoms were associated with an increased risk of falls, even after controlling for other co-factors. The CIT method leveraged us to select the most important variables to predict falls with great precision. To prevent and manage falls among the expanding and diverse older-aged population, a multilevel and cross-sectoral approach is required. Mental health, especially depression, should be dealt with greater precautions. Public health enthusiasts should focus on the physical as well as mental health of the country's older adult population.

Keywords Falls, Depression, Machine learning, India, Older adults, Conditional Inference trees, LASI

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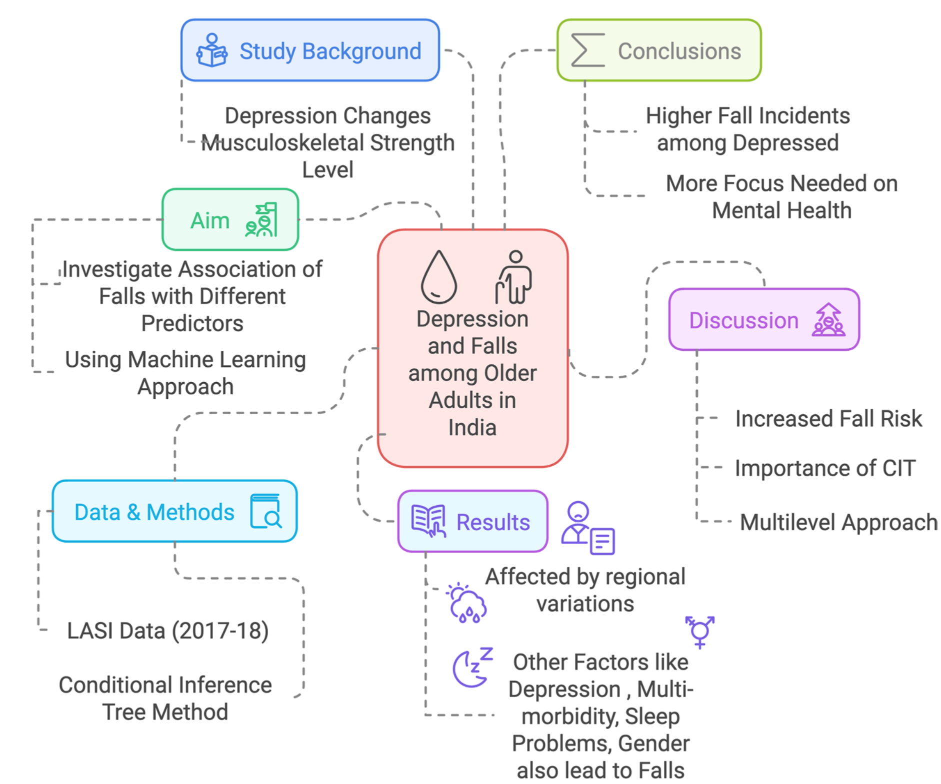
Graphical Abstract



Introduction

Falls are a major concern among older adults in India and other middle- and low-income countries with a rapidly growing aged population. It is also one of the leading causes of injury related deaths [1, 2]. For older adults, falls account for the greatest number of days with limited activity [3]. Around one-third of aged adults have experienced at least one fall every year [3]. According to a WHO report, due to falls, over 38 million Disability-Adjusted Life years (DALYs) are lost each year [4].

Most older adults, due to the gradual decrease in sensory and cognitive functions, have a significantly higher risk of falling, facing at least one fall per year [3, 5, 6]. According to World Health Organisation, a large portion of elderly people suffer from injuries or mortality due to falls [4]. Gait, balance problems, and falls are also the second major cause of deaths in adults aged 60 years and above after road traffic accident injuries [5, 7]. Falling for the first time produces fear of further falling within an individual, which results in restrictions on activities. These restrictions result in subsequent deterioration in mobility and some other motor activities, leading to disability and mental health problems [7, 8].

There are a limited number of studies trying to find out the risk factors of falls, including mental health, sleep anomalies, lack of social participation, sex, and region of residence among older adults; hence, a thorough study finding the possible association of falls and depression is important. The data available through the Longitudinal Ageing Study in India (LASI) allows us to investigate the relationship in detail. Demographic factors like gender, age, educational qualification, marital status, Activities of daily living (ADL) are found to be highly correlated to the likelihood of falls [7, 8]. This study has employed a machine learning (ML) approach to draw a valid conclusion about the underlying reasons for falls, as ML models can be tailored to individual needs, allowing for personalized interventions and recommendations that consider unique risk factors. ML method was used to test the significance of the association of different factors with greater accuracy, and for this purpose, three higher parameters were evaluated to achieve the best possible level of accuracy in prediction by the model.

Extensive research has established that depression may be an independent factor contributing to the fear of falls, dizziness, and even osteoporotic fractures [2, 5, 9–12].

India shares a prominent burden of depressive problems [11]. The Global Burden of Disease (GBD) Study India showed that around 46 million people in India had one or other depressive disorders in 2017. The prevalence was highly age-dependent and was higher among older adults [13–15]. A correlation between mental health –especially depression in elderly people and falls among them has been studied carefully, and a significant relation has been found [7, 8, 16, 17]. Severe depression in elderly people leads to a greater chance of injurious and recurrent falls [16, 18, 19], which results in an increased percentage of permanent disability and death. Depression is also among the prime factors for single falls [16], leading to recurrent falls with increased depression, anxiety, and reduced mental and physical activity. In addition to depression, studies from various regions of the world have shown a correlation of sleep anomalies with falls [20] among the older adults. Since there is an inter-correlation between sound mental health, quality sleep and sleep duration [16], an individual with poor sleep quality becomes vulnerable to fall and disability which are both falls related injury.

Social participation of the elderly people can improve the condition of depressed, and it may be an intervention to prevent fall and fall injuries [21–23]. Older age increases the risk of incident falls in both sexes, however the intensity of mediators like pain, balance, and comorbidity status differ by sex [24, 25]. It is an indication that gender should be considered in designing fall-prevention strategies.

Research from high income countries (HICs) suggest multi-morbid older adults were at a greater risk of falls than others [20, 23]. Although it is found from the available studies [26, 27] that there is a variation in the factors with respect to the region among older adults, regional variation in risk factors among older adults in India has not been thoroughly explored. This gap in the literature underlines the need for more region-specific studies to fully understand how factors like depression, sleep disturbances, and comorbidities interact with the risk of falls in different parts of India.

Considering the aforementioned, this study aims to understand the risk factors for falls leading to fall-related injury and death among older adults. The study considers independent factors faced by older adults, such as chronic diseases, sleeping disturbances, and depression, and tries to explore whether these factors contribute to falls and fall-related injuries.

Data and methods

Data

The source of the data is Individual data record of Longitudinal Ageing Study in India, (LASI) Wave 1 Survey [26] which records the individual characteristics of the sample of individuals 45 years and above as well as their spouses. LASI utilizes a multistage clustering sampling design, employing a three-stage sample design in rural areas and a four-stage sample design in urban areas. More details can be found in LASI report [26].The age of the respondent for the current study has been taken as- individuals who are 45 years and above referring to available literature [18]. The variable age is important to study since, with increase of age, physical frailty or sarcopenia [28] arises which may lead to weak gait, weakness and eventually falls. The LASI data was collected in 2017–18.

Methodology

Conditional Inference Trees, often referred to as CITs [29], have gained significant prominence in academic research due to their robustness, interpretability, and adaptability across various fields of study. These trees represent a sophisticated evolution of traditional decision trees, designed to address the limitations and challenges posed by complex and high-dimensional datasets. In the realm of academia, CITs have found widespread application in fields ranging from ecology and biology to social sciences and economics [29–32]. One of the primary reasons for their popularity is their ability to handle both categorical and continuous variables seamlessly, making them suitable for a wide range of research questions and data types.

Due to this, the method is appropriate to fulfill the aim of the study to analyze the factors and their interactions as well as the hierarchy of the factors. Further, the Conditional Inference Tree handles the numeric variables as well as the categorical variables effectively which is valuable to check for model's goodness of fit. As a result, it is the most appropriate method for the analysis. Comparison of the model was not done as it is unbalanced in its original state and as a result, the results might be misleading.

There are certain aspects of the conditional inference tree which form the base of the conditional inference forest that need to be highlighted prior to the use of the algorithm in order to define the sort of conditional inference tree to be handled. The conditional inference tree used here has its test statistic for the global and local null hypotheses. A chi-square test of association that is permuted with respect to the response values to test for significance. The Bonferroni correction is used to test for multiple hypotheses.

There are three hyperparameters that need to be evaluated which are as follows:

1. mtry: This refers to the number of variables to be sampled at each node of the CIT.
2. mincriterion: This refers to fixing the minimum *p*-value or rather, the maximum 1- p-value for the global null hypothesis.
3. ntree: This refers to the total number of trees to be constructed by the Conditional Inference Forest Algorithm.

The training of the first two hyperparameters are undertaken by the caret package via out-of-bag bagging estimated and repeated cross validation respectively.

For the hyperparameter tuning,'mtry' hyperparameter, a value of 2 was selected, resulting in an accuracy score of 1. Similarly, for the 'Min-criterion' hyperparameter, a value of 0.99 was chosen, again yielding an accuracy score of 1. These values indicate that the chosen hyperparameters performed optimally for the given dataset, achieving a high level of accuracy in the model's predictions. The values for the parameters were chosen after running optimization exercises whereby there was no improvement in the accuracy after these values.

The ntree parameter in the cforest function determines the maximum number of trees to be grown initially, but it doesn't guarantee that exactly what number of trees will be in the final forest. The algorithm employs a pruning process to select the most informative trees and may reduce the number of trees in the final forest. As a result, the ntree value is fixed at certain levels and a Conditional Inference Forest is run to establish the importance of each variable via permutation of predictor values. The average of the importance values is then taken to arrive at an average importance score which is used to build the final CIT. The grid search method was used to identify the values for the hyperparameters- mtry which ranged from 1 to 5, mincriterion which ranged from 0.9 to 0.99 and the ntree which ranged from 100 to 500. The ntree parameter was set at its default values as it provides only a guideline for the number of trees to be created, not the exact number.

The package used in R studio is the partykit package, with a Bonferroni correction applied to allow for the inclusion of multiple hypotheses.

Balancing the dataset

It is important to have a balanced sample to get a good predictive ML model. The disbalance in the algorithm may lead to a biased predictions with false accuracies in the majority class of the response variable. The raw data of ever falling in the last 2 years is distributed so that it is heavily biased towards never having a fall (30,309) versus having had fall (4757).

Splitting the sample into training and testing data

The training and testing datasets are thus created by sampling out 70% of the balanced data to create the training set while the rest 30% of the data is kept as the test set.

After balancing the response variable 'Fall', the distribution was achieved as follows. In the training data, 3,306 instances were categorized as "No", while 3,302 instances were labelled as "Yes". For the test data, there were 1,450 instances marked as "No" and 1,454 instances categorized as "Yes".

The test dataset is a subset of the balanced dataset which is of the real-world data. Given that the model is created on the training data set and then tested on the test dataset. Also, since the split of the two datasets were random, it allows for the simulation of real-world data.

Variable description

Outcome Variable

Fall- The outcome variable here refers to the event of the fall happening in the last 2 years. It is a binary taken as "Yes" and "No."

Predictors

For the primary independent variable, depression, widely known CIDI-SF scale (Composite International Diagnostic Interview-Short Form [26] was used for measurement using a series of questions for assessment:

The list of the questions can be found in Supplementary table S1.

A score of 3 or more out of 10 implies Depression.

The final variable for the existence of depression in an individual was taken as "Yes" coded as 1 and "No" coded as 0.

CIDI-SF is one of the most efficient methods of assessing depression and has been adopted by LASI for its national report hence, that was also employed in the current study.

The description of other independent variables like Age, Sex, Educational Status, Marital status, Work status, Living arrangement, Physical exercise, Health status (morbidity status), Activities of Daily Living (ADL status), Sleep disorder and Region can be found in the *supplementary Table 2.*

R studio software and Stata v.18 was used for the entire analysis.

Sample description

The sample taken for training was a randomly drawn sample from the balanced sample. It contained 70% of the records contained in the balance dataset. The training considers the rest of the data which was not included in the training sample.

The original sample of the LASI Survey was spread over 29 states and 6 Union Territories. It had a total sample size of 72,250 individuals. See Fig. 1 Data cleaning and Screening process. After cleaning the data and recoding, the total sample size was 44,066 which originally had an exceptionally low incidence of fall. The nearmiss algorithm was implemented to create a further concentrated balanced sample of 9614. The training sample consisted of 70% of randomly drawn records from the balanced sample ($N=6610$) and the test sample consisted of the remaining 30% ($N=2904$). The training and the testing datasets hereby created were similar in their distribution with regard to the various categories of the predictors as seen in case of Supplementary Table 3.

The original Sample distribution can be seen in Table 1. Further on considering, the chi-square test of association for the predictor variables with the response variable are also mentioned in the above table. From the data, it can be observed that factors of Wealth and Exercise are not significantly associated with the recurrent Falling. Similar are the association results in the training dataset in Supplementary Table 3. So, there is no risk of unnecessary bias in the modelling.

Further the variables of Exercise and Wealth were kept in the analysis as the CIT in question undertakes to test the significance of splits in the subgroups created by the tree. So, although a factor may appear insignificantly associated with the entire sample, it may show significant association in the subgroups. However, it could also be possible that these two factors may not be key factors for the overall relationship.

For the hyperparameter tuning, 'mtry' hyperparameter, a value of 2 was selected, resulting in an accuracy score of 1. Similarly, for the 'Min-criterion' hyperparameter, a value of 0.99 was chosen, again yielding an accuracy score of 1. These values indicate that the chosen hyperparameters performed optimally for the given dataset, achieving a high level of accuracy in the model's predictions.

Results

The values of the ntree varies from 50 to 300 can be seen in Table 2.

Further, important predictor values are shown in Table 3. The importance of the variables is calculated using the decrease in misclassification rate which provides a relative measure of average decrease in misclassification. The variable importance evaluation method used considers the learning sample and is conditional with a threshold of 0.9 with a permutation of 10. Here,

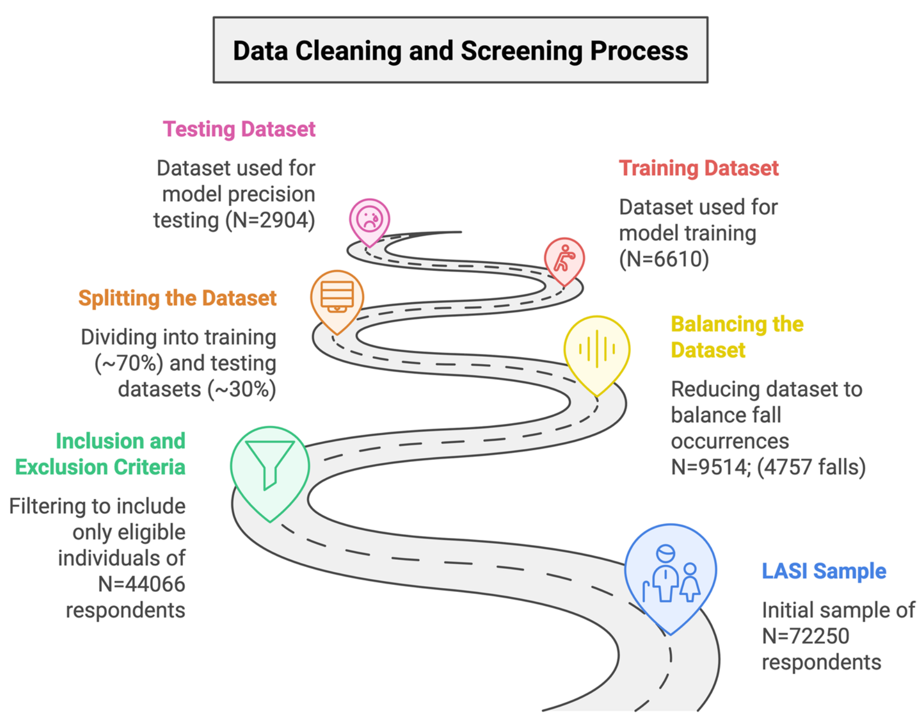


Fig. 1 Data cleaning and sample selection of the study

Table 1 Prevalence of falls by subgroup: percentage distribution in the overall sample, India (2017–18)

Predictor	Category	Prevalence of Fall ($N = 44{,}062$)	*P*-value of Chi-square test of Association of the Balanced Sample
Fall	No	89.21	
	Yes	10.79	
Wealth Quintile	Poorest	10.77	> 0.05
	Poorer	12.32	
	Middle	12.37	
	Rich	12.27	
	Richest	12.07	
Depression	No	10.92	< 0.01
	Yes	17.21	
Age	45–49	10.88	< 0.01
	50–54	10.22	
	55–59	11.50	
	60–64	13.47	
	65–69	12.28	
	70–74	13.72	
	75–79	11.16	
	> = 80	15.32	
Gender	Male	10.95	< 0.01
	Female	13.50	
Education	Primary	12.94	< 0.01
	Secondary	10.60	
	Tertiary	11.91	
Marital Status	Not Currently Married	13.62	< 0.01
	Currently Married	11.43	
Currently Working	No	12.60	< 0.01
	Yes	11.57	
Living Arrangements	Living alone	14.04	< 0.05
	Living with Family	11.17	
	Living with Family and/or others	12.75	
	Living with Others	14.52	
Does Exercise	No	10.85	> 0.05
	Yes	12.07	
Chronic Illness	None	9.85	< 0.01
	1–2 Chronic Illnesses	13.07	
	More than 2 chronic Illness	18.00	
Region	North	13.92	< 0.01
	South	9.92	
	West	11.70	
	Central	12.57	
	East	14.59	
	Northeast	8.66	
ADL	Not Significant (< 3 ADL)	11.74	< 0.01
	Significant (> = 3 ADL)	16.44	
Sleep Trouble	None	9.80	< 0.01
	Minor or Occasional	14.85	
	Frequent	19.71	

Table 2 ntree values and the measures of accuracy derived

ntree value	Accuracy (%)	F1score (*100)	Balanced Accuracy (%)	95% CI of Accuracy (%)
50	63.40	61.19	63.40	61.61-65.15
100	62.91	60.65	62.92	61.13-64.67
150	63.09	61.10	63.09	61.30-64.84
200	63.19	61.4	64.95	61.40-64.95
250	63.22	61.4	64.95	61.40-64.95
300	63.26	61.30	63.26	61.47-65.01

CI Confidence Interval

Table 3 Variable importance across ntree values and its average

Predictor\ntree	50	100	150	200	250	300	Average
Wealth	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Age	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Gender	0.01	0.02	0.01	0.01	0.01	0.01	0.01
Depression	0.01	0.01	0.02	0.02	0.02	0.01	0.02
Education	0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Marital Status	0.01	0.01	0.01	0.01	0.01	0.01	< 0.01
Health	0.02	0.02	0.02	0.02	0.02	0.02	0.02
ADL	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Living Arrangement	0	0.01	0	< 0	0.01	< 0.01	< 0.01
Region	0.06	0.06	0.07	0.07	0.06	0.06	0.06
Employment Status	0.01	< 0.01	0	< 0.01	0.01	0.01	< 0.01
Exercise	0	0	0	0	< 0.01	0	< 0.01
Sleep Trouble	0.01	0.02	0.02	0.02	0.01	0.02	0.01

ADL Activities of Daily Living

the variables do show too much variation in the classification in case of exclusion. However, this may be because the resampling introduces bias into calculation of variable importance due to the loss of information from the removed values. So, while the variable importance is used as a measure to understand the importance, it is used more in terms of understanding the level of importance rather than the actual importance. Those variables that exhibit a level of importance of more than or equal to 0.01 on average are kept in the final model. Certain variables that do not feature due to the threshold value are replaced by 0 for the 7 runs.

As it can be observed, the variables that do have some impact on the classification model are wealth, ADL, region, depression, gender, sleep trouble and health. So, the final CIT derived is shown in Fig. 2.

The confusion matrix and the results derived are given in Table 4. In the given table, the count and measures of the full CIT where all the predictors are considered are given in [-] to provide a measure of comparison. The Conditional Inference Tree reveals that the most important factor for 'Fall' is the region of residence for the current dataset. Among those individuals who are in the East and Central Regions, the next important factors are that of health and wealth respectively. There does not appear to be any significant importance of depression or sleep issues in these two regions.

Depression has a direct effect on the event of fall but only among the individuals who have one or more chronic health issues and minor or frequent sleeping troubles and reside in the North, South and West of the country. Among the individuals in this group, the presence of depression leads to falls whereas the absence of depression leads to falls due to various factors of health, gender and sleep trouble issues.

Among the individuals in the North, South, West regions without any chronic illnesses and no sleep trouble, the only important factor is that of gender and region.

The accuracy and fit of the model are moderate (as given by the F1-score). It is further observed that with reference to the full model which provides the accuracy measures of the CIT for all the predictors, this tailored model has better accuracy and precision. The tailored model on the basis of the conditional inference forest

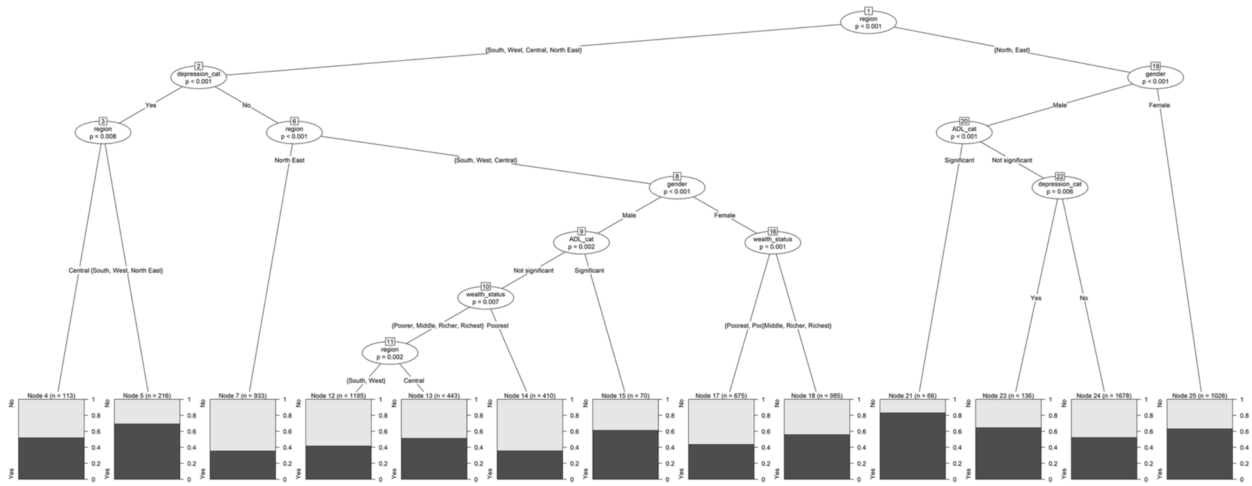


Fig. 2 Conditional Inference Tree of classification of Falls

Table 4 Confusion matrix and accuracy of the CIT developed on the test data

Response	Yes	No	Total
Prediction			
Yes	715 [732]	369 [390]	1084 [1122]
No	739 [722]	1081 [1060]	1820 [1782]
Total	1454 [1452]	1450 [1450]	2904 [2904]

Accuracy: 61.85% (60.05%–63.62%) [61.71%(59.91%–63.48)], Sensitivity: 49.17%[50.34%], Specificity: 74.55%[73.10%], Precision: 65.96%[65.24%], Recall:49.17%[50.34%], F1 Score: 56.34%[56.83%], Balanced Accuracy:61.86%[61.72%]

definitely provides a more accurate model, although the increase is very little and is accompanied by a loss in sensitivity.

A noteworthy observation is that on removing the not important predictors, the factor of ADL issues (which initially turns out to be important) does not feature in the Conditional Inference tree. This may be because ADL issues occur because of chronic illness and thus may be considered to be collinear with the factor of health as a result of which it does not appear significant in the resultant CIT.

Discussion

The study analyzed data of older adults aged 45 years and above in India suffering from falls and found region as a significant factor of falls among the older adults in each part of the country. The individuals residing in the North, South, West and Northeast regions of the country had a different set of factors that affect the incidence of fall than the East and West regions of the country. The variable 'region' encompasses many factors such as diet, climate, terrain, geographical location, availability of medical care as well as lifestyle among other things. So, it can be concluded that there is a major difference in the risk factors subject to the geographical region. Several studies discuss geography being a major determinant of falls in India [33, 34].

It is established that improper sleeping history, known as sleeping disorder is another influencing factor of falls [5, 20, 35, 36] among adults and this has been a finding of the current study, too, as the incidence of recurring falls is higher among those with minor or frequent sleeping troubles in the North, South, West and North-Eastern regions of the country. Low quality sleep affects the physical and mental health resulting in poor cognitive functioning that causes falls and increases the chances of recurring falls among the older adults [37, 38]. However, the association is seen in only certain regions of the country and not the others. This shows that sleep disorders do not uniformly affect the incidence of falls in the country; there are other factors underplaying this.

Our study also finds that older adults who have depression as an additional condition along with sleeping disturbance have a medium chance (~60%) of falls in the North, South, West and Northeast region of India. This is supported by various studies which have found that older adults suffering from depression have a high risk of falls [8, 17, 18, 39–42]. Mental health has a great impact on human behavior. Specifically, depression has a major influence on recurring falls among adults aged 45 and above. The chance of recurring fall increases more than one times among the people having depression [16]. The older adults with depressive symptoms were 80% more likely to have concerns about falling. Again, after the first fall, due to injury and fear of fall, physical functioning and social activeness decrease, and consequently, depression appear, or the conditions deteriorate [43–45].

Gender was found to be another significant factor in falls for the older adults in this study; however, it is a low-ranking factor. This is underlined by various studies [7, 16, 20, 46] which discuss women are more likely to experience depressive symptoms than men [27], which may be the reason why the results show depressive symptoms is more strongly associated with injurious falls in women [18, 28, 39, 46].

The Conditional Inference Forest shows that the variables like wealth, ADL, region, depression, gender, sleep trouble and health are more important than other variables. CIT results also show that the presence of depression does emerge as a factor but only for a particular subgroup of the sample, specifically for individuals living in the North and South regions of the country with frequent or minor sleep troubles. This implies that the presence of depression is an aggravating factor for the occurrence of recurring falls which increases the risk of recurrent falling. So, it may be viewed as a catalyst that uniformly affects the subgroup. In the absence of depression, the factors of gender and sleep troubles along with region become important.

The study finds significant 'regional contribution' (with p-value < 0.001) to falls among the older adults, specifically for those residing in the central and eastern regions of India. Residents of the central region, without any sleeping problems, depression or chronic diseases, have the highest chance of falls (~90%). Residents from the eastern part with none to one / two chronic diseases have a medium chance (~60%) of falls whereas the chance increases (~80%) if they have two or more chronic diseases. Appearance of chronic diseases among older adults is another main factor of fall. The study finds that in this region, i.e., in the central and eastern part of India, gender is not an influencing factor of fall among the older adults, but wealth and health issues are. It will be interesting to note here that the factor of wealth is not significant overall but does become significant in the subgroup of individuals residing in the Central region of the country.

This study's findings have several potential real-world applications, particularly in informing public health interventions and clinical practices aimed at preventing falls among the elderly. The results align with and contribute to existing literature, offering unique insights into the role of depression and other risk factors in fall risk. These insights can support the development of targeted screening programs and policy initiatives.

Limitations of the study

This study has certain limitations, including data constraints and reliance on a single machine learning technique, which may affect its generalizability. Specifically, using only a Conditional Inference Tree could limit the model's ability to generalize to new data, potentially leading to overfitting.

Future research could explore additional machine learning approaches and a broader range of risk factors to enhance predictive accuracy and applicability across diverse populations. Furthermore, examining potential mechanisms behind observed relationships, such as how depression may increase fall risk, can provide a deeper understanding and guide practical applications in healthcare settings. This could not be included in the study due to data unavailability.

The study is also limited to statistical analyses of fall occurrences among India's older adults; it does not investigate the root causes of region-specific differences in the probability of falls. A more in-depth study with extensive background data, such as detailed health statuses of the subjects and micro-environmental data of the specific locations, will be required to analyze the causes of the region-specific differences.

Conclusion

The surrounding conditions of a fall are intricate, multifaceted phenomenon in nature. To prevent and manage falls among the expanding and diverse aging population, multilevel and cross-sectoral approaches are required.

The current study finds that the region is the most influential factor in falls among older adults in India. Other factors influencing the incidence of falls are gender, multiple chronic diseases, and sleeping disturbance. Depression acts as a highly aggravating factor in the presence of sleep disturbance rather than as a simple influencing factor alone. The factors that lead to recurring falls and their interactions are highly specific to the region and thus in its turn, the socio-cultural context of that region. So, interventions designed to prevent or tackle the issue of recurrent falling must include the cultural context and the specific factors. Further investigation into the mechanisms of these factors is required to understand how those affect falls and how to mitigate the associated risk.

Abbreviations

ADL	Activities of Daily Living
CI	Confidence Interval
CIDI-SF	Composite International Diagnostic Interview-Short Form
CIF	Conditional Inference Forest
CIT	Conditional Inference Trees
DALY	Disability-Adjusted Life Years
HIC	High Income Countries
LASI	Longitudinal Ageing Study in India
ML	Machine Learning

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12877-025-05813-z.

Supplementary Material 1.

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Data for this study were extracted from the first wave of the Longitudinal Aging Study in India (2017-19) conducted by the International Institute for Population Sciences (IIPS) Mumbai, India. The authors are thankful to IIPS for providing the data.

Authors' contributions
MPB, JK, AM, and AA conceptualised the study. MPB and AM did the formal analysis. JK and AA wrote the first draft of the manuscript. All the authors reviewed and finalised the manuscript.

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Data availability
The study uses secondary data from LASI Wave-1 survey- collected by the nodal agency International Institute for Population Sciences (IIPS), Mumbai, on behalf of the Government of India. Data were de-identified which is publicly available to the researchers and policymakers upon formal request to the nodal agency IIPS. To access the data, a request can be made via this link- https://iipsindia.ac.in/sites/default/files/LASI_DataRequestForm_0.pdf and should be sent to the mail datacenter@iipsindia.ac.in. Further, for information related to the LASI data set Longitudinal Ageing Study in India (LASI) International Institute for Population Sciences (IIPS) (iipsindia.ac.in) website can be visited.

Declarations

Ethics approval and consent to participate
The Central Ethics Committee on Human Research (CECHR) under the Indian Council of Medical Research (ICMR) provided the ethical approval for conducting the LASI survey. Analyses and methods were carried out in accordance with relevant guidelines and regulations. The survey agencies that conducted the field survey for the data collection have collected prior informed consent (signed and oral) for both the inter- views and biomarker tests from the eligible respondents in accordance with Human Subjects Protection.

Consent for publication
Not applicable.

Competing of interests
The authors declare no competing interests.

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