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A framework for Machine Learning- based Fall from Height Prediction in Construction Industry

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ABSTRACT

The construction industry is undeniably one of the most hazardous sectors, where workers face a multitude of risks daily. Among these risks, falls from height (FFH) stand out as a significant concern, accounting for a substantial proportion of fatal and nonfatal injuries. Over the years, with the advent of advanced technologies and data analytics, there has been a growing interest in leveraging Machine Learning (ML) and artificial intelligence (AI) techniques to enhance fall risk assessment and prevention. This paper provides a comprehensive, concept-centric literature review of FFH, exploring its evolution, diverse models, the use of machine learning and artificial intelligence techniques for better assessment and prevention as well as extensive applications. This paper presents a framework for an explainable machine learning-based model for proactive FFH prediction of in construction sites. The framework leverages the predictive power of random forest classifier, a robust ensemble learning method, along with the interpretability offered by the Local Interpretable Model-agnostic Explanations (LIME) framework. It also critically addresses key challenges such as lack of transparency in the use of machine learning models in FFH predictions and its consequent effect of limiting trust among users. By evaluating the evolution and current state of FFH research, this paper reviewed the significant trends, uncovers existing gaps, and suggests potential direction for future work. This research work, therefore aims to deepen the understanding of this crucial domain in the construction industry that is receiving traction and disturbing publicity.

1. INTRODUCTION

The construction industry is undeniably one of the most hazardous sectors, where workers face a multitude of risks daily. Among these risks, falls from height (FFH) stand out as a significant concern, accounting for a substantial proportion of fatal and nonfatal injuries. According to (Febriana et al., 2022) FFH are consistently the leading cause of fatalities in the construction industry, constituting nearly one-third of all construction-related deaths. This alarming statistic underscores the urgent need for effective fall prevention strategies to safeguard the well-being of construction workers. FFH incidents inflict a devastating human cost. Workers risk life-altering injuries and potentially permanent disabilities, compromising their workability, independence, and quality of life. In the worst cases, fatalities leave families and communities grieving. The psychological impact extends beyond the injured, affecting those who witness such events. Traditional methods of assessing fall risks in the construction industry often rely on

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manual observations, safety audits, and incident reports (Oswald et al., 2018). While these methods provide valuable insights, they are often subjective, time-consuming, and prone to human errors (Shi et al., 2019). With the advent of advanced technologies and data analytics, there has been a growing interest in leveraging machine learning (ML) and artificial intelligence (AI) techniques to enhance fall risk assessment and prevention (Bates et al., 2021). Several studies have explored the application of ML and AI in predicting and preventing FFH in the construction industry. For instance, (Nadia et al., 2022) conducted an impact assessment of reinforced learning methods on construction workers' fall risk behaviors using virtual reality. Their study demonstrated the potential of virtual reality-based reinforcement learning techniques in simulating and analyzing workers' fall risk behaviors, thereby providing a more accurate and interactive approach to fall risk assessment.

The adoption of machine learning models for FFH prediction in construction is hindered by their lack of transparency, which limits trust among users (Rudin et al., 2019). FFH incidents have severe consequences, including injuries, fatalities, and psychological trauma, emphasizing the need for reliable safety measures. This study addresses these challenges by proposing an explainable AI (XAI)-based model that integrates XAI techniques to create a transparent and interpretable fall detection algorithm. The goal is to provide construction stakeholders with clear insights into the model's decision-making process, thereby fostering trust and encouraging the wider acceptance of AI-powered FFH prevention systems. This is where Explainable Artificial Intelligence (XAI) emerges as a transformative force. XAI techniques aim to demystify the decision-making processes of ML models, providing insights into how they arrive at specific predictions (Sun et al., 2023). This transparency fosters trust and empowers users to understand the factors contributing most to the model's risk assessments. (Neupane et al., 2022) In the context of FFH prevention, XAI can unveil the critical features influencing the model's identification of high-risk situations. For instance, an XAI-enabled model might reveal that worker location data, combined with sensor readings indicating unsafe work practices, significantly contribute to a high FFH risk prediction (Jagatheesaperumal et al., 2022). This granular understanding allows safety managers to tailor interventions, such as targeted safety briefings or deploying fall protection equipment in specific areas.

The integration of XAI with ML holds immense potential for revolutionizing FFH prevention strategies in construction. By fostering trust and providing actionable insights, XAI can empower stakeholders to make data-driven decisions, ultimately leading to safer construction sites and a reduction in FFH incidents. This study seeks to address these gaps by leveraging XAI to develop a proactive fall prevention model, contributing to the enhancement of safety protocols and the reduction of FFH accidents in construction sites

2. RELATED WORKS

Fall-from-height (FFH) accidents account for an extremely high proportion of accidents at construction sites with a fairly high mortality rate. (Sa et al., 2011) conducted a comparative analysis of accidents that occurred between 2011 and 2015 in three countries: the United States, Korea, and China. Accidents were found to occur frequently at construction sites, with the U.S. showing a 26% increase (from 781 to 985), while China and Korea showed a 28% decrease (2634 to 1891) and a 21% decrease (from 621 to 493), respectively. The average mortality rate was the highest in Korea (17.9 persons), followed by the U.S. and China (9.4 and 5.3 persons, respectively). The Occupational Safety and Health Administration (OSHA) requires implementing physical safety measures to reduce such accidents at construction sites (S. Lee et al., 2022). Primary protection measures include implementing guardrails, covers, safety nets, and physical safety devices, while secondary protection measures include the use of a personal fall arrest system (PFAS) whereby the impact of an FFH accident can be minimized (Peng et al., 2023). A PFAS comprises a connector, full-body harness, lanyard, and rescue line, and may prevent a person from falling when properly configured(Pomares et al., 2020). A PFAS cannot prevent FFHs but can effectively avoid fatalities from FFHs (Cheng et al., 2022). (S. Lee et al., 2022) reported that fatalities due to losing balance can be avoided when the PFAS is properly used; however, if a worker is suspended from a PFAS for a prolonged time, there is a risk of suspension trauma, orthostatic intolerance, or other serious injuries, and workers still sustain injuries due to the incompleteness of a PFAS (Lee et al., 2019). Furthermore, the effect of a PFAS is insignificant when a person falls from a height below 15 ft, and accidents occur because workers do not properly wear PFAS due to their inconvenience during work (Rey-merchán et al., 2021).

To address the limitations of interrupting the movements of workers, some studies have considered the use of visual devices (Nadhim et al., 2016) analyzed four actions on ladders using depth information measured by Kinect and classified unsafe actions with 90.9% accuracy. (Nadhim et al., 2016) defined unsafe behaviors as situations in which workers and structural supports overlap in construction. They developed an automatic computer-vision system with 90% recall and 75% precision using CNN. (Lee et al., 2019) combined computer vision with long short-term memory (LSTM) to predict unsafe actions from video data. They determined the safety of actions based on the predicted trajectories. Their model showed a mean intersection-over-union of 73.4%, mean absolute precision of 92.9% (IOU: 0.5), and mean absolute precision of 68.1% (IOU: 0.7). However, the vision-based system is not effective since workers might be obscured by structures on construction sites. Researchers have actively developed fall detection algorithms to minimize injuries in the elderly from falls using wearable sensors(Jung et al., 2020). Threshold-based methods have mainly been used for fall detection. (Jung et al., 2020) developed a fall detection algorithm with an accuracy of 92.4% and a lead time of 280.25 ± 10.29 ms, evaluated on the SisFall public dataset, and used a complementary filter to compute the vertical angles from the IMU sensor data. (Ahn et al., 2018) developed a hip protection system for the elderly, which comprises an IMU sensor, a non-gunpowder type inflator, and a wearable airbag with a threshold-based fall detection algorithm, and 100% accuracy and a 401.9 ± 46.9 ms lead time were obtained. (Koo et al., 2021) developed a post-fall detection algorithm based on machine learning using an IMU sensor. They used five different ranking algorithms to select feature subsets. The feature subsets selected by the T-score showed the best accuracy of 99.86%.

Several studies have been conducted on developing FFH detection algorithms by extending the aforementioned research. (S. Lee et al., 2022) performed near-miss fall detection based on machine learning with IMU sensor data, where the algorithm showed 86.8% accuracy in the laboratory and 85.2% accuracy outdoors. (A. Dogan et al., 2018) performed an FFH detection study by calculating the fall height from three-axis acceleration data, with an overall error rate of 10.8%. (Koo et al., 2021) developed an FFH detection algorithm by calculating the vertical velocity and the trunk angles from IMU data and reported that 100% accuracy and a lead time of 301.8 ± 87.8 ms were obtained. To increase survival rates after FFHs (Sciarretta et al., 2018), it is important to predict the risk levels of falls. (Arena et al., 2016) experimentally confirmed that the peak acceleration of the head is between 4 and 11 m/s2 during falls. The peak acceleration value is one of the key measurement factors that can affect the severity of injury (Gabriel et al., 2019).(Kim et al., 2020) proposed a study to predict the impact of falls on the elderly with the peak acceleration value. A regression analysis was performed using a deep learning algorithm based on IMU sensor data, and its results showed a mean absolute percent error of 6.69 ± 0.33% and an R-value of 0.93. The risk of FFH accidents can be represented using the peak acceleration value. Risk prediction is more necessary and challenging to discriminate since FFH accidents result in more fatal injuries.

Similarly, (Lopez et al., 2022) conducted a risk analysis of falling from heights in the growing construction industry. Their study employed statistical and machine learning models to identify the key factors contributing to fall incidents and to develop predictive models for assessing fall risks. The findings of their study highlighted the importance of integrating various risk factors, such as worker experience, safety training, and environmental conditions, into a comprehensive fall risk assessment framework. Identifying and classifying the factors causing fall-from-height accidents is crucial for developing effective prevention strategies. (M. Arif et al., 2022) conducted a study focusing on the identification of fall events and classification of the factors causing fall from height accidents in the construction industry. Their research employed data mining and classification algorithms to analyze and categorize the contributing factors of fall incidents. The study identified several critical factors, including inadequate safety measures, lack of training, and human error, which significantly increase the risk of falls from height. In addition to identifying and classifying fall risk factors, predicting the severity of falling risks for workers at height is equally important for implementing targeted prevention measures. (Chen and Luo, 2016) and (Chen and Luo, 2016) developed severity prediction models of falling risk for workers at height using advanced machine learning techniques. Their study utilized historical accident data and various ML algorithms to predict the severity of fall risks based on factors such as the height of the fall, the worker's position, and the safety equipment used. The predictive models developed in their study demonstrated high accuracy in assessing the severity of falling risks, thereby enabling more effective allocation of resources and implementation of preventive measures. While machine learning models hold immense potential for predicting FFH risk in construction, their "black box" nature can be a significant hurdle. As (Rudin et al., 2019) aptly points out, the lack of transparency in these models hinders trust and the effectiveness of preventative measures. Stakeholders in construction need to understand the "why" behind the model's predictions to implement targeted interventions.

2.1 Causes and Effects of Fall from Height

(Cole, 2019) OSHA regulations require fall protection at varying heights depending on the industry, but worker discomfort with personal protective equipment (PPE) can lead to unsafe practices. (Vosoughi et al., 2020) Other contributing factors include inadequate training, poor equipment, unsafe work environments, and communication issues. These accidents cause significant human suffering, with fatalities, injuries, and psychological impacts on workers and their families. Economically, FFH accidents lead to project delays, medical costs, lost productivity, and damage reparations. The causes and effects of FFH accidents as outlined by (Studies, 2023), focusing on five categories of causes and the humanitarian and economic consequences of these incidents.

2.1.1 Risk Behavior

1. *Personal protective equipment (PPE):* Several studies underscore the crucial role of Personal Protective Equipment (PPE) in mitigating the dangers of falls from height (FFH). (Lopez et al., 2022) conducted research that specifically emphasizes the prevalence of FFH fatalities within the US construction industry. Their analysis revealed a concerning trend: a significant portion of these fatal incidents involved workers who were not documented as utilizing proper PPE. This finding highlights a critical safety lapse, as appropriate PPE can significantly reduce the severity of fall injuries or even prevent them altogether. Similarly, (Nadia et al., 2022) conducted research focused on FFH accidents in Malaysia. Their investigations identified a conspicuous absence of fall arrest systems as a major contributing factor.
2. *Rush to work:* One of the most concerning behavioral factors contributing to fall-from-height (FFH) incidents is the prevalence of rushing at work. When faced with time constraints and pressure to complete tasks rapidly, workers may be more likely to prioritize speed over safety. This prioritization can lead to a disregard for established safety protocols or a failure to utilize proper fall protection equipment. Research by (Rodrigues et al., 2022) provides empirical evidence to support this connection. Their study identified financial constraints and the pressure to finish jobs quickly as significant factors contributing to FFH accidents.
3. *Mistakes in making decisions:* One of the most concerning aspects of fall hazards in construction work is the potential for human error in decision-making. Instances of poor judgment, such as working too close to an edge without appropriate fall protection measures in place, can have devastating consequences. Research by (Manzoor et al., 2021) emphasizes the crucial role of cultivating a strong safety culture within construction environments.

2.1.2 Unsafe Conditions

1. *The open edge of the building*: One of the most critical fall hazards in high-rise construction environments is the presence of unguarded edges. A recent study by (Arif et al., 2021) exemplifies this danger. Their investigation into a fall accident on a high-rise building project highlighted the critical role of proper edge protection systems in preventing such tragedies.
2. *Hole in the floor:* One of the most prevalent fall hazards in construction environments

involves inadequately addressed floor openings. Uncovered or poorly marked holes, such as those created for elevator shafts, utility access, or other construction purposes, present a substantial risk of falls for workers. (Nowobilski and Hoła, 2023) aptly highlight the critical importance of effectively identifying and demarcating these hazards.

3. *Unsuitable scaffold:* Highlighting the inherent risks associated with falls from height, a crucial contributing factor lies in the utilization of unsuitable scaffolding. Faulty construction or improper assembly practices significantly elevate the probability of falls for workers on these temporary structures..
4. *Lack of lighting:* One of the significant environmental hazards contributing to falls in construction work environments is inadequate lighting. When faced with poor lighting conditions, workers experience compromised visibility. This diminished ability to see their surroundings clearly can have a two-fold effect, significantly increasing the risk of falls. Firstly, the inability to discern potential tripping hazards on the ground, such as uneven surfaces, debris, or loose materials, can lead to missteps and subsequent falls. Secondly, poor lighting can hinder the accurate perception of distances. This can cause workers to misjudge the depth of drops or the height of platforms, potentially resulting in falls from elevated work areas. Research by (Manzoor et al., 2021) emphasizes the critical role of proper illumination at construction sites, particularly during periods of low natural light or when working in enclosed spaces. By ensuring adequate lighting is provided throughout the worksite, the risk of falls due to impaired visibility can be significantly mitigated, promoting a safer work environment for construction personnel.
5. *Poor housekeeping:* In the pursuit of workplace safety, maintaining a well-organized and clutter-free environment plays a crucial role in preventing falls. Research by (Nadia et al., 2022) underscores this critical aspect, highlighting the significant contribution of poor housekeeping to slip, trip, and fall incidents. The presence of clutter and debris on work surfaces creates uneven walking paths, concealed obstacles, and potential tripping hazards.

2.2.3 Management and Organization

1. *Training:* One significant factor contributing to construction site fall incidents is the inadequacy of training provided to workers regarding fall prevention measures and safe work practices. This lack of preparatory instruction leaves them poorly equipped to identify and effectively mitigate potential fall hazards within their work environment. Research has consistently underscored the importance of comprehensive safety training programs in bolstering construction workers' knowledge and awareness. Studies conducted by (Acion et al., 2017) and others serve as prime examples, demonstrating the critical role that such training plays in fostering a safety-conscious workforce. By equipping workers with the necessary skills to recognize falls and implement appropriate preventative measures, these programs can significantly reduce the likelihood of fall-related accidents in the construction industry.

2. *Management commitment to the work program:* One crucial determinant of a construction site's fall prevention success hinges on the unwavering commitment of its management team to the established safety work program. A safety-centric company culture fostered and actively championed by leadership plays a pivotal role in ensuring worker well-being. Research by (Vosoughi et al., 2020) underscores this critical link. Their findings demonstrate a clear correlation between a lack of management commitment to safety protocols and an alarming rise in the number of fall-related incidents within the construction industry.
3. *Lack of work procedures:* The inherent dangers associated with construction work, especially tasks involving heights, necessitate the implementation of well-defined and documented work procedures. The lack of such established protocols can have detrimental consequences, fostering confusion amongst workers and significantly increasing the risk of unsafe practices. This notion is further underscored by (Manzoor et al., 2021), who highlight the critical role of standardized procedures in mitigating such risks. By outlining clear and consistent steps for various construction activities, particularly those at elevated levels, these

procedures ensure a uniform approach that prioritizes safety.

4. *Lack of supervision:* The absence of effective supervision on construction sites is a well-documented contributing factor to falls from height (FFH). When supervisors fail to adequately monitor worker activity, unsafe practices can become commonplace, significantly increasing the risk of falls. Research by (Shi et al., 2019) underscores the crucial role of proper supervision in mitigating FFH hazards. Effective supervisors are not only responsible for ensuring workers adhere to established safety protocols, such as proper harness usage and utilizing fall protection equipment, but also for actively identifying and addressing potential falls present in the work environment.
5. *Non-provision of PPE:* The absence of proper Personal Protective Equipment (PPE) presents a significant safety hazard for workers, particularly those at risk of falls from height. Research by (Nadia et al., 2022) underscores the critical role of employers in mitigating these risks. Their study highlights the legal and ethical responsibility of employers to furnish their workforce with adequate fall protection equipment.

6. *Fatigue:* One significant contributing factor to falls from height (FFH) is worker fatigue. When workers experience physical and mental exhaustion, their cognitive abilities become impaired. This translates to a heightened risk of errors in judgment, specifically regarding safety protocols and hazard identification. Additionally, reaction times significantly decrease, hindering the ability to react swiftly and effectively in precarious situations. Research conducted by (Manzoor et al., 2021) underscores the critical role of implementing proper work schedule management strategies..

2.2.4 Job Factor

1. *Material Preparation:* During construction projects, material preparation and handling at elevated locations pose a significant safety hazard. Research by (Arif et al., 2022) underscores the critical role of meticulous planning and the utilization of designated lifting equipment in mitigating falls associated with material management at height. (Manzoor et al., 2021) highlight the need for proper fall protection measures specific to the type of structural work being undertaken.
2. *Scaffolding Malfunction:* The construction industry presents inherent safety risks, and scaffolding erection and dismantling are particularly hazardous activities. (Nowobilski et al., 2023) rightly highlight the critical role of adhering to established safety protocols and employing qualified personnel throughout the scaffolding lifecycle. In conclusion, prioritizing proper scaffolding construction and dismantling practices, as advocated by (Nowobilski et al., 2023), is an essential step towards safeguarding workers from potentially life-threatening fall hazards.

2.2.5 External Factors

1. *Weather:* Construction work inherently takes place outdoors, exposing workers to various weather conditions that significantly impact fall hazards. Adverse weather events like rain, snow, or strong winds can dramatically transform work surfaces, rendering them slippery and unstable. This heightened instability significantly increases the likelihood of falls from heights. Research by (Manzoor et al., 2021) underscores the critical importance of proactively adjusting work practices to mitigate these risks..

2.3 *Concept of Artificial Intelligence (AI) and Machine Learning*

Artificial Intelligence (AI) is a specialized area within computer science that focuses on developing systems capable of performing tasks typically requiring human intelligence, such as decision-making, problem-solving, and learning (Adenuga et al., 2022). Recent advancements have seen AI applications flourish in various industries, particularly in scenarios demanding high precision and minimal human intervention. The integration of AI into various sectors has significantly enhanced productivity and accuracy, particularly in the domain of predictive analytics, such as fall prediction in construction settings. The ability to anticipate and mitigate risks associated with falls has become increasingly important as populations age and healthcare systems strive for preventive care measures. In the context of big data, where vast amounts of information are processed, AI and its subset, machine learning, offer robust tools for analyzing complex datasets and providing actionable insights (Sciarretta et al., 2018). Machine learning algorithms, particularly those employed in predicting events such as falls, have shown high accuracy and reliability, thereby supporting clinical decisions such as those presented by (Akazue et al., 2023) for prediction of survivability of Diabetes Melitus, Okpakoet al., (2019) for the prediction and managing of comorbid diseases using neutrosophic logic and machine learning, (Okpako et al., 2021) for decision support system for effective diagnosis of liver disease using neutrosophic logic

This adaptive capability allows computers to recognize patterns and relationships in large datasets, facilitating predictions and decision-making processes based on empirical data (Thisovithan et al., 2023). A machine learning model, according to (Lundberg et al., 2020), is essentially a trained system capable of identifying specific patterns. This process involves training the model with a dataset and an algorithm to generalize and predict outcomes based on new, unseen data.

Machine learning has transformative impacts across various industries, including healthcare, where it is used for diagnostic predictions, treatment personalization, and risk assessment. In the context of fall prediction, different machine learning models, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and others, is utilized to predict the likelihood of falls in patients, thereby aiding in preventive measures.

2.3.3 Random Forest Classifier

Random Forest (RF) classifiers have emerged as a robust and versatile method in machine learning for both classification and regression tasks. Boateng et al. (2020). The concept was presented by Leo Breiman in 2001, which extended the idea of decision trees into an ensemble method that aggregates multiple decision trees to improve classification accuracy and control overfitting Breiman (2001). RF classifiers avoid overfitting by ensuring that the individual decision trees are not highly correlated and by applying the Strong Law of Large Numbers to guarantee convergence (Boulesteix et al. 2018). RFs aim to reduce the correlation between trees while maintaining their strength (Jahani et al. 2022). While AdaBoost adjusts sample weights in response to classification errors, RF introduces randomness in feature selection, leading to similar accuracy but with increased robustness to noise and outliers (Yusuf et al. 2021). The lower correlation among trees in RF contributes to its resilience against noisy data, which often affects AdaBoost's performance (Wang et al., 2024).

While Random Forests offer high accuracy and robustness, there are some drawbacks. One of the challenges is interpretability. The "black-box" nature of ensemble methods like RF makes it difficult to interpret individual tree decisions (Gerón et al., 2023). To mitigate this, several techniques, such as variable importance scores and partial dependence plots, have been developed to offer insight into how RF makes predictions (Greenwell et al., 2017). Rana G., (2017) also highlighted the computational burden when dealing with extremely large datasets or when the number of trees becomes excessively large. Although RF is generally faster than boosting methods like AdaBoost, the computational complexity increases linearly with the number of trees and features (Wyner et al., 2017).

2.5 Black Box vs White Box Machine Learning Models

In the field of machine learning, particularly within applications involving safety-critical areas such as construction, the ability to explain predictive outcomes to stakeholders is paramount. This capability is crucial for the development of trustworthy AI systems, especially when predicting potentially hazardous events like falls from heights. The selection of an appropriate machine learning model often involves a trade-off between accuracy and interpretability. This dichotomy is typically characterized by 'black-box' and 'white-box' models.

2. *Black-box Models and Accuracy:* Black-box models, such as neural networks, gradient boosting machines, and complex ensembles, are known for their high predictive accuracy. However, these models are inherently opaque, making it challenging to discern the importance of individual features or understand the interactions between them. The internal mechanics of these models are often inscrutable, which can hinder stakeholders' trust and the model's practical application in scenarios where transparency is critical (Ribeiro et al., 2016).

- *White-box Models and Interpretability:* In contrast, white-box models, such as linear regression and decision trees, offer greater interpretability. These models allow for a clearer understanding of how predictions are derived, as they provide explicit relationships between inputs and outputs. However, they may lack the predictive power of more complex models, particularly when dealing with intricate data patterns involving non-linear interactions among features (Guide et al., 2021).

2.6 Optimizing Machine Learning Models

Optimizing machine learning models is crucial for improving their predictive accuracy and generalizability. This process often involves hyperparameter tuning, which adjusts the learning algorithm's settings to achieve the best performance on a given task (Bergstra et al., 2012). In the context of fall prediction, optimization techniques such as grid search, random search, and more sophisticated methods like Bayesian optimization and evolutionary algorithms can be employed to fine-tune model parameters and enhance predictive capabilities (Bengio et al., 2014).

2.7 Explainable Artificial Intelligence (XAI)

2.7.1 What is Explainable AI?

Explainable artificial intelligence (XAI) refers to a collection of procedures and techniques that enable machine learning algorithms to produce output and results that are understandable and reliable for human users (Neupane et al., 2022). Explainable AI is a key component of the fairness, accountability, and transparency (FAT) machine learning paradigm and is frequently discussed in connection with deep learning. Organizations looking to establish trust when deploying AI can benefit from XAI. XAI can assist them in comprehending the behavior of an AI model and identifying possible problems like AI.

2.7.2 Origin of Explainable AI

The origins of XAI can be traced back to the early days of machine learning research when scientists and engineers began to develop algorithms and techniques that could learn from data and make predictions and inferences (Doran et al., 2018). As machine learning algorithms became more complex and sophisticated, the need for transparency and interpretability in these models became increasingly important, and this need led to the development of explainable AI approaches and methods.

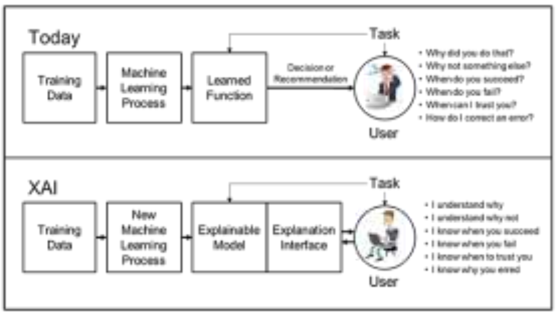

Figure 2.1 XAI diagram (source: https://www.darpa.mil/program/explainable-artificial-intelligence)

One of the key early developments in XAI was the work of (Rai et al., 2020), who introduced the concept of *causality in machine learning*, and proposed a framework for understanding and explaining the factors that are most relevant and influential in the model's predictions. This work laid the foundation for many of the explainable AI approaches and methods that are used today and provided a framework for transparent and interpretable machine learning.

Another important development in explainable AI was the work of (Ignatiev et al., 2020) *LIME (Local Interpretable Model-agnostic Explanations)*, which introduced a methodfor providing interpretable and explainable machine learning models. This method uses a local approximation of the model to provide insights into the factors that are most relevant and influential in the model's predictions and has been widely used in a range of applications and domains.

One of the main themes emphasized is the need for trustworthy AI systems. A study (Ignatiev et al., 2020) highlights that XAI is crucial for building trust by making AI decision-making more transparent and accountable. This aligns with broader ethical considerations in AI development, where explainability is essential for ensuring responsible and unbiased AI applications. Trust is fundamental in human interaction, and it's no different with AI systems. When we don't trust a system, we're less likely to use it or rely on its outputs. XAI helps bridge this trust gap by providing users with insights into how AI models arrive at their decisions (Marcin C., 2020). By understanding the reasoning behind these decisions, users can assess the fairness, reliability, and appropriateness of the AI's output. Furthermore, XAI can help hold AI systems accountable for their actions. If an AI system makes a harmful or incorrect decision, XAI can provide explanations that can be used to identify and rectify the underlying cause of the problem. In this way, XAI contributes to the development of more ethical and trustworthy AI systems (Hall et al., 2022).

The need for interpretability goes beyond general-purpose models. While general techniques exist, their effectiveness can vary depending on the application. (Stefano M., 2013) addressed this by developing specialized methods for interpreting forecasting models. These methods illuminate how specific features contribute to the final prediction, enabling users to understand the rationale behind the forecast. Similarly, (Brusa et al., 2023) focused on machine fault diagnosis, where understanding feature contributions within the model is crucial for targeted maintenance interventions. These works highlight the importance of tailoring interpretability techniques to the specific task and data, considering factors like the type of predictions being made and the desired level of detail for actionable insights.

Case studies, like the one by (Vishwarupe et al., 2022), offer valuable perspectives on XAI by showcasing its practical applications and real-world benefits. By examining specific use cases, this work demonstrates how interpretable machine learning techniques can empower users with deeper insights and enhance decision-making processes. Case studies can serve as crucial bridges between theoretical advancements in XAI research and their practical implementation in diverse applications. For instance, a case study might explore how an interpretable model is used to identify fraudulent transactions in a financial setting. By understanding the features that contribute most to the model's fraud classification, analysts can gain valuable insights into emerging fraud patterns and develop more effective detection strategies. Similarly, a case study in the healthcare domain might examine how an interpretable model is used to predict patient outcomes. By explaining the model's reasoning behind a particular prediction, doctors can gain a deeper understanding of the factors influencing patient health and make more informed treatment decisions. These are just a few examples of how case studies can illuminate the practical value of XAI in various real-world scenarios.

Deep learning models, despite their impressive performance, pose unique challenges in terms of interpretability due to their complex architecture and non-linear relationships between input features and outputs. (Samek et al., 2017) explored techniques for visualizing and interpreting deep learning models. They presented methods like sensitivity analysis and layer-wise relevance propagation, which provide insights into the inner workings of these complex neural networks. By visualizing the importance of input variables and decomposing model predictions, researchers can gain a deeper understanding of how deep learning models arrive at their decisions.

(Rudin et al., 2019) Challenge the prevailing reliance on black-box models in AI development. Their work demonstrates that interpretable models can often achieve performance on par with black boxes while maintaining crucial transparency. This highlights the importance of prioritizing interpretability as a core design principle from the very beginning of AI system creation. Instead of attempting to explain opaque models after the fact, focusing on inherent interpretability fosters the development of trustworthy and readily understandable AI systems – a crucial step towards a future of responsible and collaborative human-AI interaction.

2.7.2 Machine Learning and Fall from Height

The construction industry faces a persistent and critical challenge: FFH (Zlatar et al., 2019). These incidents remain a leading cause of severe injuries and fatalities for construction workers, posing a significant threat to their well-being. However, the landscape of construction safety is evolving alongside technological advancements(Sciarretta et al., 2018). The rise of ML offers immense potential for developing proactive solutions to mitigate FFH.

Building upon the need for systematic preventative strategies,(Guo, 2018) made a significant contribution by introducing an ontology specifically focused on control measures for FFH in construction. This ontology serves as a foundational framework by categorizing and classifying various preventative approaches. By providing a structured understanding of these control measures, Guo et al.'s work paved the way for more effective FFH prevention strategies.

Standardized training programs have been investigated as a potential approach to reducing FFH within the construction industry. Research by (Zhong et al., 2023) explored the effectiveness of these programs, finding that they play a crucial role in equipping workers with the necessary knowledge and skills to identify and mitigate fall hazards. Standardized training programs ensure consistency in the information delivered to workers across different construction companies and project sites. This consistency helps to ensure that all workers have a baseline understanding of fall safety procedures and best practices, regardless of their experience level or specific role on a project.

(Samad et al., n.d.) addressed the crucial issue of fall event identification and classification in construction. Their work sheds light on the various factors contributing to FFH accidents, providing valuable insights into potential risk areas for targeted mitigation strategies. Further contributing to a comprehensive understanding of FFH causality,(Vosoughi et al., 2020)leveraged the Analytical Hierarchy Process (AHP) to systematically analyze the multifaceted causes of these incidents. Their research highlights the importance of considering a range of contributing factors, such as worker behavior, environmental conditions, and equipment deficiencies, when developing preventative measures. By delving deeper into the root causes of FFH accidents, these studies pave the way for the development of more effective safety interventions in the construction industry.

(M. A. I. Arif et al., 2021)survey XAI techniques to address the limitations of opaque AI models. XAI methods bridge the gap between human understanding and complex algorithms, providing explanations for AI decisions in a way that is comprehensible to humans. This fosters trust in AI systems and promotes the development of responsible AI applications.

(Machlev et al., 2022) explore XAI for power systems, aiming to address the "black box" nature of machine learning (ML) models. XAI techniques provide insights into model decisions, fostering trust and enabling optimization. Challenges include DL complexity, explainability requirements, and performance trade-offs. The paper reviews common XAI methods and their applications in power systems.

(Chen et al., 2016) recognized the potential of predictive analytics for fall risk assessment in construction. They proposed severity prediction models to assess fall risk for workers at height, demonstrating the value of data-driven approaches in proactively identifying and mitigating FFH incidents. This focus on proactive risk assessment aligns with the broader body of research that emphasizes preventative measures.

(Huang et al., 2003) conducted a valuable analysis of construction worker fall accidents, highlighting the critical need for robust risk assessment methods to prevent such occurrences (Rivara et al., 2000; Huang et al., 2003). By building on these foundational works, this research project aims to explore how Machine Learning can be harnessed to develop more sophisticated and proactive fall risk assessment models. By leveraging machine learning algorithms and their ability to identify complex patterns within data sets, this project has the potential to move beyond basic severity prediction and progress toward real-time risk assessment and targeted preventative actions.

This paper by (El Marhraoui et al., 2023) investigates the use of interpretable artificial intelligence (XAI) for fall risk detection in elderly populations. Early identification of fall risk is essential for preventing injuries and improving quality of life. Traditional fall risk assessment methods like the TUG test are subjective, inaccurate, and limited in monitoring capabilities. AI-powered fall risk detection using wearable sensors (e.g., IMUs) offers continuous monitoring and personalized risk assessment based on gait data. However, health professionals need to understand the reasons behind AI predictions for effective interventions. This study proposes an XAI-based approach for fall risk detection using IMU sensors. The model employs a visual self-attention mechanism to pinpoint critical moments with high fall probability, such as rapid vertical acceleration. This interpretability allows healthcare professionals to validate medical hypotheses, develop targeted prevention strategies, and improve patient trust in AI-powered healthcare tools. Overall, the research promotes the development of accurate and interpretable AI models for fall risk detection. The XAI approach fosters trust in AI and empowers healthcare professionals to personalize fall prevention strategies, ultimately improving patient care and safety.

Program et al. (2023) this study investigates the causes of FFH accidents in Saudi Arabia's construction industry. Common causes were identified via literature review and categorized into four areas: unsafe acts, unsafe conditions, communication barriers, and management commitment. A questionnaire targeting construction professionals explored these causes. Analysis (91 responses) revealed "unsafe acts" as the most prominent category, with lack of training, safety inspections, and communication between stakeholders being the top three causes of FFH accidents. The study suggests that safety programs, inspections, and improved communication can reduce FFH accidents.

Doran et al., (2018) argues that explainable AI (XAI) is crucial for understanding complex AI models and proposes a new way to categorize XAI approaches. The paper identifies four levels of explainability: opaque systems (no explanation), interpretable systems (mathematical analysis), comprehensible systems (user-driven explanations from symbols), and a novel concept, truly explainable systems, which use automated reasoning to generate explanations without human intervention. The paper also explores how different AI fields approach explainability and discusses desirable traits for XAI systems, such as trust, safety, and fairness. Overall, Doran's work advances the discussion on XAI by highlighting the importance of reasoning and proposing a new category that moves beyond human-driven explanation creation.

Mankodiya et al., (2022) this paper proposes a wearable sensor-based fall detection system with explainable AI (XAI) for improved user trust and transparency. The system uses an LSTM model trained on multi-sensor data to achieve accurate fall detection, and LIME to explain the model's decisions. This approach addresses the limitations of existing methods by using multiple sensors and offering interpretability. The system has the potential to enhance safety for older adults living independently.

3. ANALYSIS OF THE EXISTING SYSTEM

Effective fall prevention strategies to safeguard the wellbeing of construction workers is a major concerns in the construction industry, it is therefore imperative to have a system that will enhance fall risk assessment and prevention by leveraging machine learning(ML) and artificial Intelligence(AI) techniques . Many existing systems have (Lee et al., 2022) employed different approaches in solving this phenomenal problem in construction sites, yet there is still room for improvement so as to handle the disastrous effect and cost associated with it.

A detailed review and analysis of the existing system of was carried out to bring to fore areas that needs improvement in order to tacckle the problem. The paper reviewed the following:

i. The approaches and methods used in the existing system
ii. The decision making process
iii. Support for transparency in decision making process

Architecture of the Existing System

The existing system of lee et al. (2022) was used where they recruited 20 healthy adult males from Yonsei University (mean age: 24.8 years). Participants with musculoskeletal problems were excluded. The study collected triaxial acceleration and angular velocity data from participants wearing an IMU sensor at the T7 vertebrae during various movements (walking, falling forward). A dummy was used for high-hazard falls (>2 meters).The data was pre-processed for training deep learning models. 70% of human data and 60% of dummy data were used for training, with the remaining data for testing. Two key features were extracted: acceleration and gyro sum vector magnitudes (ASVM, GSVM). Eight features in total were used to train the models. A 0.9-second window before the peak ASVM was analyzed. Three deep learning models (1D-CNN, 2D-CNN, 3D-CNN) were developed using Python 3.9 and TensorFlow 2.9.0. Hyperparameter optimization ensured optimal performance. The models' performance was assessed using Mean Absolute Error (MAE) and Mean Squared Error (MSE) to quantify the difference between predicted and measured peak acceleration values.

A typical architecture of the existing system is shown in Fig 3.1.

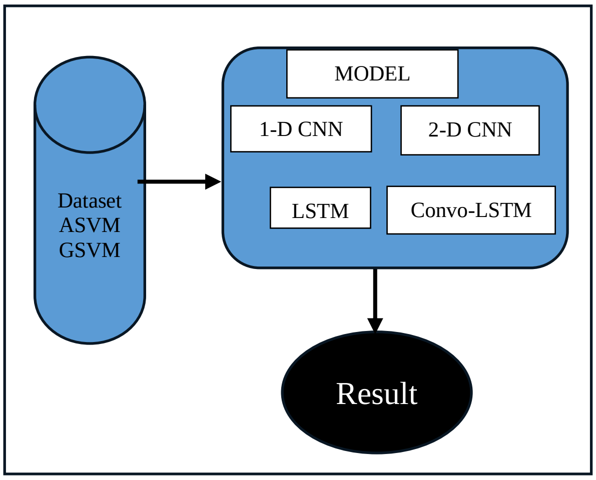

Figure 3.1 Architecture of the Existing System (source:(Lee et al., 2022)**)**

3.2.1 Limitation of the Existing System

1. Limited Dataset: The study is based on a small dataset collected from 20 subjects, which may not cover the entire range of possible movements in real-world construction sites. This limits the generalizability of the system.
2. Data Imbalance: The system faced challenges with data imbalance, as fewer high-hazard fall movements were available compared to non-fall movements. This affects the performance of some models, especially LSTM and 2D-CNN, leading to underestimation of high-risk falls.
3. Dummy Data for High-Risk Falls: For safety reasons, a dummy was used for high-hazard falls, which may not accurately capture the nuances of human movements, potentially leading to discrepancies in real-life applications.
4. Sensor Placement: The IMU sensor is placed only at the T7 position, which may limit the detection of certain types of movements or falls. Additional sensors might be needed to cover more complex scenarios.
5. Overfitting in Some Models: The system uses early stopping and dropout layers to prevent overfitting, but the issue is still prevalent in some models, particularly in cases where the dataset is limited.

The machine learning model (CNN) used lacked transparency in its decision-making process. This can be a concern for users and construction professionals who rely on the system's outputs for critical decisions. To address this limitation, we propose an enhanced system that integrates Explainable AI (XAI) with the existing approach. This combined system aims to improve fall prediction accuracy while simultaneously enhancing transparency and trustworthiness by explaining the model's predictions. By incorporating XAI, users and construction workers can gain insights into the factors that influence the model's decisions, fostering trust and confidence in its effectiveness.

1.3 Analysis of the Proposed System Model

The proposed system for proactive fall prediction in construction sites integrates a Random Forest Classifier with a Lime Tabular Explainer, focusing on creating an explainable AI-based machine learning model. This hybrid approach leverages the predictive power of Random Forests, a robust ensemble learning method, along with the interpretability offered by the LIME framework.

3.3.2 *Development of the Proposed Model*

The model development utilizes the Random Forest Classifier, an ensemble method known for its effectiveness in handling complex data patterns. Random Forests operate by constructing multiple decision trees during training and outputting the mode of the classes for classification tasks. This method is particularly advantageous in dealing with the high-dimensional and noisy data often encountered in construction site safety monitoring. The LIME (Local Interpretable Model-agnostic Explanations) framework enhances the model's interpretability by explaining the predictions of the Random Forest. LIME operates by approximating the model locally with interpretable models, thus providing insights into the contribution of different features towards the prediction of falls.

3.3.3 Architecture of the Proposed System

The architecture of the proposed system, depicted in **Figure 3.2**, illustrates the integration of the Random Forest Classifier with the LIME framework. The process begins with the Random Forest Classifier receiving input data, which it processes through multiple decision trees to make predictions. The resulting predictions are then analyzed using LIME to provide feature-level explanations. LIME operates by:

1. Generating a new dataset consisting of perturbed samples around the instance to be explained.
2. Using these samples, fits a simple, interpretable model (such as a linear model) locally to approximate the predictions of the Random Forest.
3. Providing insights into which features have the most significant impact on the prediction, thereby highlighting potential risk factors associated with falls.

This combined approach not only enhances the model's predictive capabilities but also ensures that the predictions are transparent and interpretable, crucial for safety-critical applications. The

proposed system's architecture ensures a continuous feedback loop where model predictions and explanations can be used to refine safety protocols and training procedures on construction sites, thereby proactively mitigating the risk of falls.

3.3.4 Algorithm of the Proposed System

An algorithm is a step-by-step blow of how the procedure is carried out. The algorithm for this study is outlined as follows.

Data Preprocessing Phase involves preparing the raw data for model training and evaluation.

1. Data Cleaning:
   - Handling Missing Values: Missing values are addressed using appropriate techniques such as imputation or removal.
   - Outlier Detection and Removal: Outliers, which can significantly impact model performance, are identified and removed or corrected.
   - otherwise.

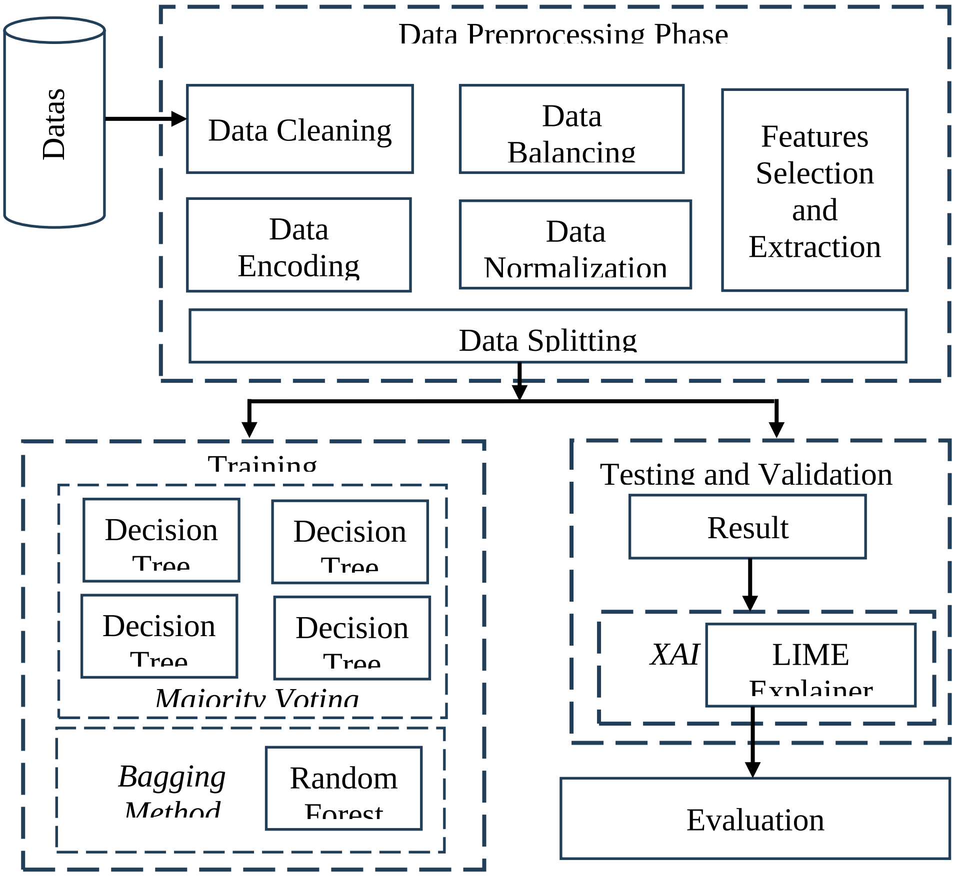

Figure 3.2 Proposed System Architecture

2. Data Encoding:

2. One-Hot Encoding: Categorical features are converted into numerical representations using one-hot encoding. This technique creates a new binary feature for each category, with a value of 1 indicating the presence of that category and 0
3. Data Balancing:
    - SMOTE (Synthetic Minority Over-sampling Technique): This technique addresses class imbalance by generating synthetic samples for the minority class (i.e., fall incidents).
    - SMOTE-Tomek: This technique combines oversampling and undersampling to balance the dataset. It oversamples the minority class and undersamples the majority class while considering the Tomek links between samples.
4. Data Normalization:
    - Min-Max Normalization: This technique scales numerical features to a specific range (e.g., 0 to 1). This ensures that features with different scales contribute equally to the model.
5. Data Splitting:
    - The dataset is divided into training and testing sets. Typically, a 70-30 split is used, with 70% of the data allocated for training and 30% for testing.
6. Feature selection and extraction phase aims to identify the most relevant features and extract eaningful information from the data.
    - Recursive Feature Elimination (RFE): This wrapper method iteratively removes features that have the least impact on the model's performance.
    - Chi-Square Test: This filter method assesses the statistical significance of the association between categorical features and the target variable.
7. The model training phase utilizes decision trees as the base learners, with multiple decision trees trained independently on various subsets of the training data. To improve robustness, a majority voting mechanism is applied to aggregate the predictions from these individual trees, where the most common prediction is chosen. This output is then enhanced using the bagging technique, specifically through the random forest ensemble method, which combines these decision trees to generate a final, more accurate result.
8. The trained model is evaluated on the testing set to assess its performance.

I. Performance Metrics:
    - Accuracy: Proportion of correct predictions.
    - Precision: Proportion of positive predictions that are actually positive.
    - Recall: Proportion of actual positive cases that are correctly identified.
    - F1-Score: Harmonic mean of precision and recall.
    - ROC-AUC: Area under the Receiver Operating Characteristic curve.
    - Confusion Matrix: Visual representation of the model's classification performance.

2. Local Interpretable Model-Agnostic Explanations (LIME) as an XAI provides explanations for individual predictions by approximating the model's decision-making process with a simpler model.

4. CONCLUSION

In this paper, an analysis of the existing systems was carried out and some limitations were highlighted for consideration. To make proper, reasonable, and appropriate prediction of fall from height in construction sites, the decision making process must be explainable as that will ensure its transparency. It is hoped that there will be an obvious improvement in the system performance in terms of handling the explainability and transparency of its prediction. Therefore, this paper proposed a framework for a machine learning based fall from height prediction using random forest and LIME. This will ensure that decisions or predictions are explained to ensure transparency in the decision making process. Future work will delve into the implementation of the framework and the result of the implementation and its evaluation will be provided.

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