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ELDERLY FALL DETECTION USING UNSUPERVISED TRANSFORMER MODEL

I. Ursul

Applied Mathematics Department,
Ivan Franko National University of Lviv,
1 Universitetska St., UA–79090 Lviv, Ukraine
ivan.ursul@lnu.edu.ua

This study explores the development of an unsupervised Transformer model for fall detection among the elderly. It aims to help address the critical need for reliable fall detection systems in an aging global population. Traditional methods, limited by accuracy and privacy concerns, require innovative approaches. The research employs unsupervised learning techniques to analyze accelerometer data, aiming to enhance detection results without compromising privacy. The Transformer model's performance, assessed through Mean Squared Error and Root Mean Squared Error, demonstrates a high degree of efficacy in reconstructing accelerometer data, which is crucial for identifying falls as anomalies. Results indicate that the model's precision is very close to supervised models, with MSE and RMSE values suggesting significant accuracy. This approach reduces the reliance on extensive labeled datasets, a common challenge in fall detection research. Hence, it offers a practical solution in real-world scenarios where labeled data is scarce. The study's findings underscore the potential of unsupervised learning models in advancing fall detection technologies. This is promising in improving healthcare outcomes for the elderly and paving the way for broader applications in activity monitoring and anomaly detection.

Keywords: Fall Detection, Unsupervised Learning, Transformer Model, Accelerometer Data, Elderly Care, Anomaly Detection, Geriatric Healthcare.

Introduction

The prevalence of falls among the elderly has emerged as a critical concern in geriatric care, highlighting the necessity for effective fall detection systems [1]. Statistically, falls are identified as a leading cause of accidental or unintentional injury deaths worldwide, particularly among individuals aged 65 and above [2]. The consequences of such incidents are complicated, encompassing immediate physical injuries [3]. Moreover, there are many long-term psychological effects, such as the fear of falling again, which can significantly diminish the quality of life and independence of the elderly [4]. The severity of this issue is further heightened by the aging global demographic, which emphasizes the urgency for advanced and reliable fall detection mechanisms [5]. Traditional fall detection methods primarily revolve around manual reporting and observation, which have limitations, notably the inability to provide timely assistance, worsening the risk [6]. This situation requires exploring technological solutions that can offer real-time monitoring and instantaneous detection of falls.

In recent years, sophisticated technologies, particularly in Machine Learning (ML) and sensor-based systems, have opened new possibilities for fall detection [7]. With its ability to learn from and predict data, ML presents a promising solution for recognizing fall patterns.

Two primary sources of data have been the focus of contemporary research in this field: sensor-based time series data and video surveillance data [8]. Sensor-based systems, often wearable or embedded in the living environment, capture physiological and movement data, offering a less intrusive and privacy-preserving approach. However, these systems have been critiqued for their limited accuracy, especially in differentiating between actual falls and fall-like activities [9]. Conversely, video-based fall detection, utilizing algorithms to analyze visual data, has demonstrated higher accuracy [10]. However, this method deals with significant privacy concerns and computational demands, making it less favorable in real-world applications [11]. This contrast in the effectiveness and acceptance of these methods underscores a significant gap in the current research. Hence, there is a need for innovative approaches that combine both techniques ʼstrengths while addressing their shortcomings.

The current literature highlights a critical gap in the research on fall detection: the need for a solution that combines the accuracy of video-based systems with the privacy and efficiency of sensor-based approaches. Exploring unsupervised learning techniques in processing sensor data presents an innovative route to address this gap. By utilizing the potential of unsupervised algorithms, there is an opportunity to significantly improve the accuracy of sensor-based fall detection systems without encroaching on privacy or incurring prohibitive computational costs. This research seeks to fill this gap by proposing a novel, hybrid approach that could set a new standard in fall detection technology, balancing accuracy, privacy, and computational efficiency. To develop and validate a novel hybrid fall detection system that utilizes both sensor-based technologies ʼstrengths, employing supervised and unsupervised machine learning techniques to enhance accuracy, preserve privacy, and optimize computational efficiency in elderly care.

1. Refine unsupervised learning algorithms on sensor data to improve fall detection accuracy, reducing false positives and negatives.
2. Develop privacy-preserving methods for sensor-based fall detection, focusing on anonymization and minimal data usage.
3. Design and evaluate a model integrating sensor and video data insights, optimizing accuracy, privacy, and efficiency.

The motivation for this research is the need to enhance elderly care through advanced technological interventions, specifically in fall detection. With the global demographic trend skewing towards an aging population [12], the frequency of fall-related incidents and their associated healthcare burdens are predicted to escalate. The limitations of current methodologies further emphasize this need. While sensor-based fall detection systems offer a degree of privacy and simplicity, their efficacy is often undermined by a higher rate of false alarms. This is restricting them from accurately distinguishing between actual falls and fall-like activities. On the other hand, despite their superior accuracy, video-based systems need help with privacy concerns and computational demands, which limit their practicality in real-world settings.

This research aims to bridge this gap by exploring the potential of unsupervised learning techniques in analyzing sensor-based data to enhance fall detection accuracy without compromising privacy. The goal is to develop an innovative, hybrid approach that combines the strengths of both sensor and video-based systems, thereby offering a robust, efficient, and privacy-conscious solution. This research aligns with the technological advancements in ML and data analysis. It will be prepared with the ethical imperative to safeguard the dignity and independence of older people, making it a crucial and timely contribution to geriatric care and technology.

Literature Review

The inception of fall detection systems can be traced back to manual methodologies, which relied on the vigilance of caregivers or self-reporting [13]. This approach has limitations, primarily due to its reactive nature. The reliance on reactive reporting of fall incidents resulted in significant delays in response, aggravating the risk of severe injuries [14]. The inefficacy of these methods in providing immediate assistance highlighted the critical need for more proactive and automated fall detection systems [15]. The historical context of fall detection is not just a testament to the evolution of care for the elderly [16]. It underscores the necessity for technological intervention in enhancing the quality and responsiveness of geriatric care [17].

As the field progressed, the advent of sensor-based technologies marked a significant leap forward in fall detection methodologies [18]. The integration of wearable devices with accelerometers, gyroscopes, and ambient sensors started a new era of continuous monitoring [19]. These sensor-based systems were designed to detect sudden changes in motion indicative of a fall, facilitating a quicker response than traditional methods [20]. However, despite these advancements, sensor-based fall detection systems faced challenges [21]. A notable limitation was their propensity to generate false positives, which can be seen [22]. It shows their inability to distinguish between actual falls and fall-like activities accurately. This lack of precision undermined the reliability of these systems and raised concerns regarding their practical utility in real-life scenarios.

Integrating ML algorithms with sensor-based systems introduced a promising solution to the challenges above [23]. ML's capability to discern patterns in complex datasets offered a potential improvement in the accuracy of fall detection systems. By analyzing sensor data, these algorithms could learn to differentiate between falls and non-fall activities more effectively [24]. However, this approach relies on the availability of extensively labeled datasets, which were challenging to compile given the infrequent nature of falls [16]. The dependency on supervised learning algorithms needed reevaluating the methodologies employed in fall detection. Researchers are exploring alternative approaches that could circumvent the limitations imposed by the need for labeled data [25].

Conversely, video-based fall detection systems emerged as an alternative that leveraged computer vision technologies to monitor video footage for fall incidents [26]. These systems offered higher accuracy in detecting falls by analyzing visual cues and patterns indicative of a fall [27]. Despite their effectiveness, video-based systems introduced new challenges, primarily related to privacy concerns [11]. The continuous surveillance required by these systems raised ethical questions, particularly in monitoring private spaces such as homes and personal living areas [28]. The intrusion into personal privacy posed by video-based systems was a significant problem, limiting their acceptance and widespread adoption despite their technical capabilities.

The current research on fall detection has a hybrid approach that combines the strengths of both sensor and video-based systems while addressing their respective limitations [29]. The exploration of unsupervised learning techniques in sensor data analysis presents an innovative pathway toward enhancing the accuracy of fall detection systems without infringing on privacy. This approach seeks to leverage the inherent capabilities of unsupervised algorithms to improve the precision of fall detection, thereby reducing the reliance on extensive labeled datasets and mitigating the privacy concerns associated with video surveillance. The move towards a hybrid model underscores the ongoing efforts to refine fall detection technologies. This research aims to develop systems that are accurate, efficient, and respectful of the privacy and dignity of the elderly population.

Materials and Methods

Data Pre-processing. A research-oriented document's dataset and pre-processing section typically begin with an overview of the data collection and preparation process, which is essential for subsequent analysis or model development. This study utilizes accelerometer data, likely gathered to analyze various physical movements or activities. The data manipulation and analysis are facilitated by foundational libraries that efficiently handle numerical arrays and data structures. The initial step involves organizing the data within a structured directory, ensuring a systematic approach to data storage and accessibility. This organization is critical for maintaining a clean and manageable dataset, especially when dealing with multiple categories or data types.

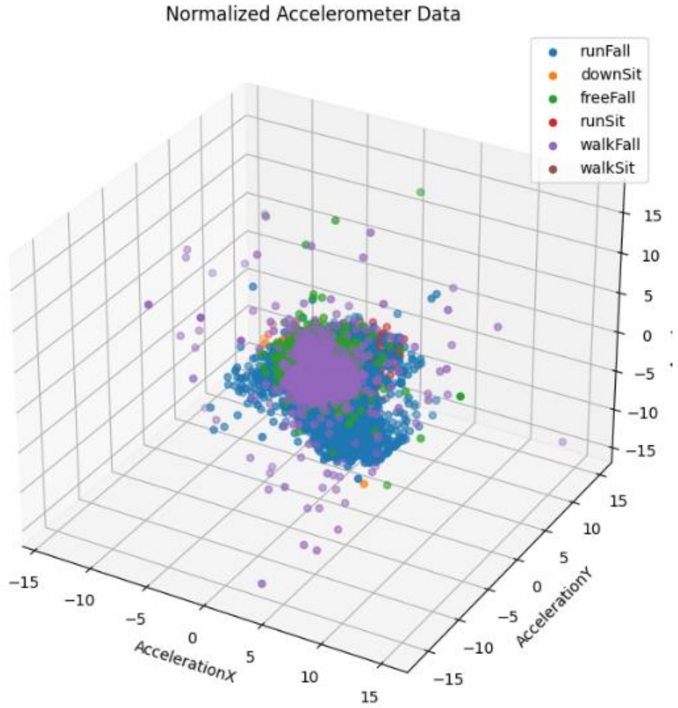

Fig. 1. A visualization of Accelerometer for falls detection.

Data categorization is achieved by defining a set of labels that represent distinct activities or movements captured by the accelerometer. These labels are crucial for the classification task, as they provide a semantic understanding of the data, enabling the differentiation between various movements, such as fall transitions from running to sitting or walking to sitting. Following the categorization, the study proceeds with the pre-processing of data, a pivotal step in preparing the dataset for analysis. This involves reading the accelerometer data from multiple files, each corresponding to a specific label, and integrating them into a cohesive structure. The integration process consolidates the data and ensures that each data point is accurately labeled, reflecting its type of movement.

Normalization of the accelerometer data is a critical pre-processing task aimed at standardizing the data values across all dimensions (*X*, *Y*, and *Z* axes). This standardization is achieved by adjusting the data to have a mean of zero and a standard deviation of one. Such normalization is critical for removing biases due to varying scales or units of measurement, thereby making the data more homogeneous and suitable for comparative analysis. Finally, the study aggregates all pre-processed data into a unified dataset. This consolidation is instrumental in creating a comprehensive dataset encompassing all labeled movements, facilitating an analysis or the development of predictive models. The unified dataset serves as the foundation for exploring patterns, understanding the characteristics of different movements, and developing algorithms capable of accurately classifying or predicting the types of activities based on accelerometer data.

Supervised Learning. Logistic Regression is a statistical model that estimates the probability that a given input point belongs to a particular class. The version used here is suited for multi-class classification, where the dataset contains more than two classes. In the fall detection problem, Logistic Regression uses the One-vs-Rest (OvR) strategy for multi-class classification. This means that for each class, a binary classifier is trained to distinguish that class from all other classes, effectively converting the multi-class problem into multiple binary classification problems. The model distinguishes between various states, such as a fall (*F*) and other non-fall activities (*NF*), by employing accelerometer data (a) as the primary input. The equations describing this process are as follows:

The probability that a given accelerometer reading a_i signifies a fall is computed using the logistic function:

$$P(F_i \mid a_i) = \frac{1}{1 + \exp(-(\alpha_{F0} + \alpha_F^T a_i))} \tag{1}$$

where α_F represents the coefficients associated with the fall class and α_{F0} is the intercept term. Under the One-vs-Rest strategy, a binary classifier is constructed for the fall class *F*, defined as $g_F(a)$, which is operationalized as:

$$g_F(a) = \begin{cases} 1, & \text{if } P(F_i \mid a_i) > P(NF_i \mid a_i) \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Thereby, the multi-class classification problem is transformed into multiple binary classification scenarios. For a test accelerometer reading a_{test}, the probability of it being associated with a fall is given by the softmax function:

$$P(F \mid a_{test}) = \frac{\exp(\alpha_{F0} + \alpha_F^T a_{test})}{\sum_{k \in (F, NF, \ldots)} \exp(\alpha_{k_0} + \alpha_k^T a_{test})}, \tag{3}$$

where the denominator ensures normalization by summing over all possible classes. The classification of a new accelerometer reading a_{test} into a specific event category $\hat{E}$ is determined by:

$$\hat{E} = \arg\max_{k} P(k \mid a_{test}) \tag{4}$$

By selecting the event type k with the maximum probability. This approach effectively addresses the challenge of multi-class classification within the domain of fall detection by leveraging the capabilities of Logistic Regression in conjunction with the One-vs-Rest strategy, thereby facilitating the discrimination between fall and non-fall events based on accelerometer data. LSTM networks are designed to recognize patterns in data sequences, such as time-series data, making them ideal for tasks like fall detection from accelerometer data. They can learn long-term dependencies due to their internal mechanisms (such as gates) that regulate the flow of information. In the domain of fall detection, the application of Long Short-Term Memory (LSTM) networks represents a unique approach to capturing temporal dependencies inherent in accelerometer data. The LSTM model is structured to process sequences of accelerometer readings a_t, where t indexes time, thereby recognizing patterns indicative of a fall event (F) versus non-fall activities (NF) The mathematical representation of this process includes. The LSTM network ingests a sequence of accelerometer readings $a_{1:T}$ overtime T, encapsulating the temporal dynamics through hidden states h_t computed as:

$$h_t = \mathrm{LSTM}(a_t, h_{t-1}; \theta) \tag{5}$$

where θ denotes the parameters of the LSTM layer and h_{t-1} is the hidden state from the previous time step, initializing with $h_0 = 0$. To mitigate overfitting, a dropout mechanism is applied to the hidden states h_t randomly nullifying a fraction of the elements, thus enhancing the model's generalization capability:

$$h_t = \mathrm{dropout}(h_t; p), \tag{6}$$

with p representing the dropout rate. The final time step's hidden state h_T is then fed into a dense layer, culminating in a softmax output that provides the probability distribution over potential events, including falls:

$$P(E \mid a_{1:T}) = \mathrm{softmax}(\mathrm{Dense}(h_T, \phi)), \tag{7}$$

where E denotes the event type and ϕ the parameters of the dense layer. The model's prediction $\hat{E}$ for a sequence $a_{1:T}$ is determined by selecting the event type with the highest probability from the softmax output:

$$\hat{E} = \arg\max_{E} P(E \mid a_{1:T}) . \tag{8}$$

This LSTM-based framework is adept at discerning the subtle and complex temporal patterns associated with fall events from accelerometer data, leveraging the sequential nature of the input to provide a robust solution for fall detection. Including dropout and applying a dense layer with SoftMax activation function is critical in refining the model's predictive efficacy, ensuring that the LSTM network can accurately classify fall and non-fall events in a real-world setting.

Unsupervised Learning. In unsupervised fall detection using a Transformer-based model, the approach involves identifying anomalies in accelerometer data, where deviations from typical patterns indicate potential falls. The mathematical formulation of this model, adapted for the fall detection problem, is outlined through the following equations:

$$e_t = W_e a_t + b_e , \tag{9}$$

where a_t represents the accelerometer data at time t, e_t is the embedded representation, W_e is the weight matrix of the embedding layer, and b_e is the embedding bias vector. This transformation projects the input data into a higher-dimensional space conducive to identifying complex patterns. The Self-Attention Mechanism can be described as:

$$SA_t = \text{softmax}\left(\frac{(W_q e_t)(W_k e_t)^T}{\sqrt{d_k}}\right)(W_v e_t) , \tag{10}$$

where SA_t denotes the self-attention output for time t, W_q, W_k and W_v are the weight matrices for query, key, and value in the attention mechanism, respectively, and d_k represents the dimensionality of the key vector. This equation allows the model to weigh the importance of different time steps based on their relevance to the current context. The Position-wise Feed-Forward Network can be expressed as:

$$FFN_t = \max(0, W_1 SA_t + b_1)W_2 + b_2 , \tag{11}$$

where FFN_t is the output of the feed-forward network at time t, W_1, W_2 are the weights and b_1, b_2 are the biases of the feed-forward layers. This network applies further non-linear transformations to the self-attention outputs. The Anomaly Detection through Reconstruction can be expressed as:

$$\hat{a}_t = W_0 FFN_t + b_0 , \tag{12}$$

where $\hat{a}_t$ is the reconstructed accelerometer reading at time t and W_0, b_0 are the weights and biases of the output layer, respectively. The model aims to minimize the discrepancy between $\hat{a}_t$ and a_t, with significant deviations suggesting anomalies that could indicate falls. Loss for Anomaly Detection can be expressed as:

$$L = \frac{1}{T}\sum_{t=1}^{T}\left\| a_t - \hat{a}_t \right\|^2 . \tag{13}$$

This loss function quantifies the model's performance by measuring the mean squared error between the original and reconstructed accelerometer data over time T. Anomalies, or potential falls, are detected as instances where the reconstruction error significantly exceeds a predefined threshold. The Transformer-based model for unsupervised fall detection is formalized through these equations, leveraging the self-attention mechanism to capture complex temporal relationships within the data and identifying falls as anomalies characterized by significant deviations in the reconstructed signal. The Transformer model uses a complex architecture that includes the following components.

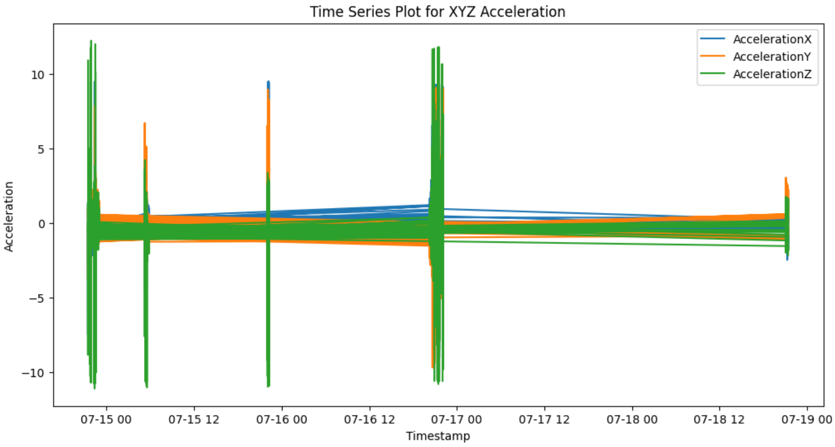

Fig. 2. The time series plot of data after pre-processing g it for unsupervised adoption

In the anomaly detection framework for fall detection, the training process is meticulously designed to optimize the model's ability to discern falls from normal activities through reconstruction accuracy. The Mean Squared Error (MSE) loss function is pivotal, quantifying the discrepancies between the original input data and its reconstructed counterpart, thereby gauging the model's proficiency in data replication. The Adam optimizer is deployed for its efficacy in handling sparse gradients and adaptively adjusting learning rates, enhancing the model's convergence towards optimal parameters. To ensure the robustness of the training, gradient clipping is employed, constraining the norm of parameter gradients to a maximum of 1, which is instrumental in averting potential instabilities in training dynamics. Upon completion of the training phase, the model transitions to an evaluation mode, modifying the operational characteristics of specific layers like Dropout and Batch Norm to suit inference conditions, ensuring consistent performance across training and inference stages. The evaluation encompasses the computation of reconstruction loss for individual samples, with those exhibiting a loss exceeding a predetermined threshold flagged as anomalies indicative of potential falls.

Results and Evaluation

Logistic Regression Performance. The Roc scores of the Logistic Regression model are provided in the figure below. The AUC values for the classes are all above 0.45 but below 0.6, suggesting that the model has learned to some extent to distinguish between classes, but there is significant room for improvement. In a perfect classifier, we would expect the curves to be closer to the top-left corner of the plot. The class with the label 'runSit 'with an AUC value of 0.56 seems to be the best distinguished by the model, while the class 'walkSit 'with an AUC value of 0.46 is the least distinguishable from the others based on the model's learned parameters. So, it can be said that the Logistic Regression model demonstrates moderate classification ability on this dataset. However, the AUC values indicate that the model may struggle with certain classes. This could be due to various factors, including feature selection, class imbalance, or inherent similarities between classes, making them difficult to distinguish with a linear model. Further model tuning, feature engineering, or a more complex model could improve classification performance.

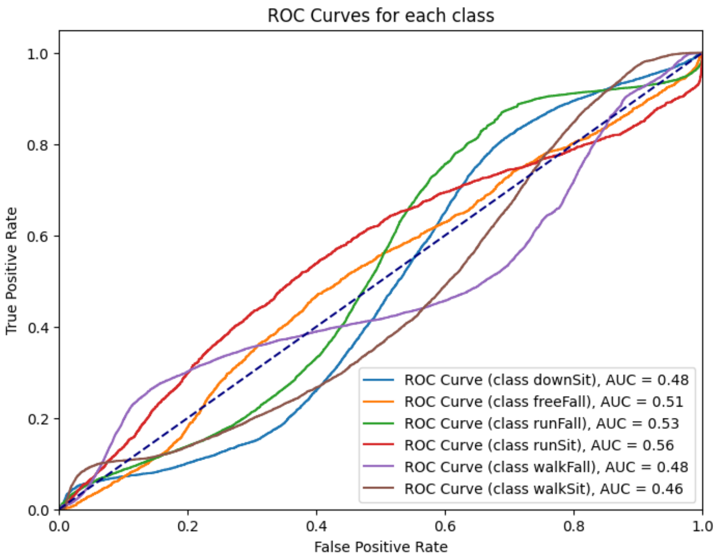

Fig. 3. Logistic Regression performance for fall detection.

LSTM Performance. From the graph's ROC-AUC scores, the LSTM model performs exceptionally well, with AUC scores ranging from 0.83 to 0.99 across the classes. High AUC scores indicate that the model has a strong predictive ability for differentiating between the various classes of movements captured by the accelerometer data.

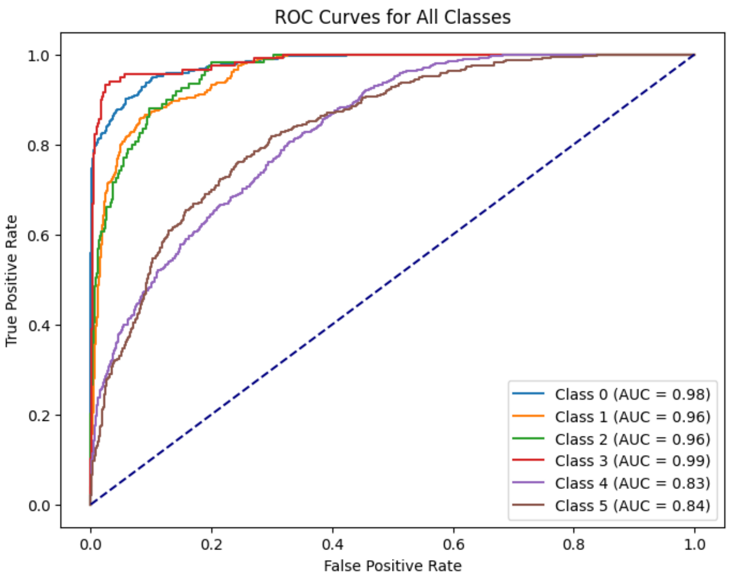

Fig. 4. The performance of the LSTM model for fall detection.

Unsupervised Transformer Model Performance. The empirical analysis yielded promising results in exploring unsupervised mechanisms for fall detection utilizing Transformer models. The evaluation focused on the model's proficiency in reconstructing accelerometer data, with the MSE and RMSE serving as primary metrics for assessing the model's performance. The Transformer model achieved an MSE of 0.09685, indicating a modest discrepancy between the predicted and actual accelerometer readings. This error level suggests that the model can capture the essential patterns within the data, which is crucial for accurately identifying falls as anomalies. Moreover, the RMSE, which provides a more intuitive measure of the average prediction error in the same units as the data, was recorded at 0.0984. Given the normalized nature of the accelerometer data, where values are expected to be close to zero, an RMSE below 0.1 implies a relatively high degree of accuracy in the model's predictions.

In fig. 5. the vertical axis, labeled 'Reconstruction Error', quantifies the error between the actual data point and its reconstructed version as produced by the transformer model. The transformer model attempts to learn the normal pattern of the data, and the reconstruction error is indicative of how well the data point fits this learned pattern. The blue plot signifies the reconstruction error for each data point. The lower values of blue plot suggest that the data point is closely aligned with the model's learned representation of normal behavior. The horizontal red line represents the anomaly threshold. This threshold is a pre-determined value that acts as a cutoff point above which data points are considered anomalies. In other words, any sequence index where the blue line (reconstruction error) exceeds the red line (anomaly threshold) is flagged as anomalous.

Fig. 5. Reconstruction Error in Anomalous Fall Detection

The red vertical lines highlight these anomalies by marking the sequence indices where the reconstruction error surpasses the threshold. This visual cue makes it easier to identify periods where the frequency or intensity of anomalies is higher. From a research standpoint, the density and height of the red vertical lines provide insights into the model's sensitivity and the nature of the anomalies detected. A high density of red lines may indicate a period of increased anomaly activity or could suggest that the threshold is set too low, causing the model to over-identify anomalies. On the other hand, if there are very few red lines, it could mean that the period is largely normal or the threshold is too high, leading to under-identification of anomalies.

These findings are significant in unsupervised fall detection, where the primary challenge lies in distinguishing falls from normal daily activities without explicit labeling. The Transformer model's ability to closely reconstruct the input data suggests a nuanced understanding of the temporal dynamics and patterns characteristic of fall events instead of non-fall activities. It is, however, imperative to interpret these results within the broader framework of fall detection requirements. The sensitivity and specificity of the anomaly detection mechanism must be carefully calibrated to ensure that potential falls are accurately identified without an excessive rate of false alarms. Determining an optimal threshold for anomaly detection derived from the reconstruction error remains a critical factor in the practical deployment of this model. Furthermore, the robustness of these results should be validated through comprehensive cross-validation procedures, ensuring the model's consistent performance across diverse data segments. Collaborations with domain experts in geriatrics and fall prevention could provide additional insights into the clinical relevance of the error margins observed.

Comparative Analysis. In developing a fall detection system, the task often pivots on the availability of labeled data, which is not always feasible to acquire in large volumes necessary for traditional supervised learning approaches. In such scenarios, unsupervised learning provides a compelling alternative, allowing the model to discern patterns and anomalies without needing pre-labeled instances. The results of the unsupervised Transformer model, indicated by the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), showcase a high level of performance in reconstructing and evaluating the accelerometer data for fall detection. The MSE value of 0.09685330560045408 and the RMSE of 0.09841407704208482 suggest that the model's predictions are in close agreement with the actual measurements. These results are particularly encouraging as they approach the effectiveness typically seen in supervised models, as evidenced by the ROC curves for all classes with AUC scores ranging from 0.83 to 0.99.

The ROC curves, a graphical representation often used in evaluating supervised learning models, display the model's ability to accurately classify different types of falls. The proximity of the AUC values to 1 indicates excellent model performance in differentiating between classes, such as distinguishing a fall from other activities, under a supervised framework. Contrasting these results with the unsupervised model's performance suggests that the unsupervised approach is viable and competitive. This is significant in fall detection, where the exhaustive labeling of fall events is impractical due to their infrequency and the sheer diversity of fall scenarios that can occur in real-world settings. The ability of the unsupervised model to perform closely to its supervised counterparts while being less reliant on extensive labeled data represents a substantial advancement in fall detection methodologies. Thus, the comparison underscores the unsupervised model's potential as a less data-dependent solution, capable of operating effectively in environments where labeled data is scarce or incomplete. This advancement holds promise for real-world applications where the collection of comprehensive labeled datasets is challenging, making the unsupervised approach a vital contribution to the domain of fall detection.

Conclusion

The study presents an unsupervised Transformer model for fall detection that demonstrates a high degree of efficacy, closely mirroring the performance of supervised models. With an MSE of 0.0968 and an RMSE of 0.0984, the model exhibits substantial precision in reconstructing accelerometer data, a task crucial for accurately identifying falls as anomalies. This precision is notably comparable to the accuracy of supervised models, as reflected by the AUC scores from the ROC analysis, ranging between 0.83 and 0.99 across various classes. This resemblance in performance is particularly noteworthy given the challenge of obtaining extensive labeled datasets in fall detection. The unsupervised approach mitigates the dependency on labeled data, addressing a significant bottleneck in developing robust fall detection systems. Using the inherent patterns within the data, the Transformer model facilitates the detection of falls with reduced reliance on pre-classified instances. Thus, enhancing the model's utility in practical, real-world scenarios where labeled data is limited. The unsupervised model represents a pivotal step towards creating sustainable, scalable, and less data-intensive solutions for fall detection. This promises substantial healthcare and geriatric care benefits and paves the way for broader applications in activity monitoring and anomaly detection.

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РОЗРОБКА ТА ОЦІНКА НЕКЕРОВАНОЇ МОДЕЛІ НА ОСНОВІ TRANSFORMER ДЛЯ ВИЯВЛЕННЯ ПАДІНЬ СЕРЕД ЛІТНІХ ЛЮДЕЙ

І. Урсул

Кафедра прикладної математики,
Львівський національний університет імені Івана Франка,
вул. Університетська, 1, 79090 Львів, Україна
ivan.ursul@lnu.edu.ua

У даному науковому дослідженні проводиться детальний аналіз розробки та впровадження некерованої моделі на базі трансформера для ідентифікації випадків падінь серед осіб похилого віку. Основною метою цієї роботи є сприяння створенню ефективних та надійних систем для автоматизованого визначення падінь, що може мати значний вплив на підвищення безпеки та якості життя літніх людей. Враховуючи існуючі обмеження за точністю виявлення та забезпеченням конфіденційності, які характеризують традиційні підходи, акцент робиться на потребі в розробці інноваційних методологій. У дослідженні використовуються методи некерованого машинного навчання для обробки та аналізу даних з акселерометрів, метою яких є не тільки покращення точності виявлення аномалій, але й збереження приватності інформації про користувачів. Аналіз ефективності моделі трансформера, заснований на оцінці середньоквадратичної помилки, демонструє її високу продуктивність у точній реконструкції даних акселерометра, що є ключовим для надійної

ідентифікації падінь як аномалій. Результати підкреслюють, що точність запропонованої моделі є порівнянною з тією, яку забезпечують контрольовані моделі, при цьому вказуючи на високу ступінь точності, засновану на значеннях середньоквадратичної помилки. Представлений підхід знижує залежність від об'ємних маркованих наборів даних, переборюючи одну з основних проблем, яка часто виникає при дослідженні систем виявлення падінь. Це відкриває шлях до розробки практичних рішень для сценаріїв реального життя, де доступ до маркованих даних обмежений або недоступний. Висновки нашої роботи висвітлюють потенціал застосування некерованого навчання у сфері покращення технологій для виявлення падінь, пропонуючи нові можливості для сфери охорони здоров'я через поліпшення систем моніторингу активності, виявлення аномалій та забезпечення безпеки літніх осіб.
Ключові слова: виявлення падінь, некероване навчання, модель трансформера, дані акселерометра, догляд за літніми людьми, виявлення аномалій.

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