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A Clustering-Aided Approach for Diagnosis Prediction: A Case Study of Elderly Fall

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***Abstract*—Data-driven diagnosis prediction has been adopted in clinical decision support systems. However, only a few studies have focused on non-supervised clustering approaches to building a high-quality patient data set. This study focused on a clustering-aided approach to diagnosis prediction. We leveraged clustering-aided machine learning models to predict elderly falls. First, we used patients' risk factors to build a feature set. We found that a clustering-aided approach could aggregate patient factors that shared similar clinical and demographic characteristics. Subsequently, a K-means clustering approach significantly improved the data set quality. Overall, our study demonstrated that clustering approaches improve the prediction performance of elderly falls. A clustering-aided approach can be applied to similar clinical healthcare practices to potentially improve elderly care.**

Index Terms*—*Clinical Decision Support, Clustering Analysis, Machine Learning, Clinical Informatics, Diagnosis Prediction

I. Introduction

Elderly-focused care has become a significant issue for the healthcare system due to the aging population [1]. Elderly falls are one of the major causes of mortality and morbidity among people over 60 years of age [2]. There is an imperative need for an approach to predict and prevent elderly falls in clinical practice. Clinical factors play an important role in clinical decision support systems. Key clinical factors include age, gender, impaired balance and gait, polypharmacy, and a history of previous falls [3]. A clinical decision-making model can predict the risk of falls using these clinical features. A machine learning prediction model can quantify the risk of falls for the elderly [4] and prevent elderly falls.

The quality of electronic health records (EHR) is essential in clinical decision-making systems. A well-built feature set can improve prediction performance [4]. Traditionally, data set quality improvement can be completed using two approaches: 1) selecting risk factors from EHRs to build a targeted feature set and 2) defining a patient sample for machine learning models. Currently, several feature selection techniques, such as feature importance and principal component analysis, have been adopted for data-driven diagnosis prediction [5]. However, only a few studies have explored patient sample selection [6]. It is possible to find associations with similar patient characteristics using the clustering approach. A clustering approach can find patients of similar ages, with similar social habits, and with similar physical health conditions. A clustered patient data set shows a greater similarity of clinical and demographic characteristics. Therefore, the clustering approach can generate a high-quality patient set that overcomes data sparsity issues for machine learning algorithms to increase predictive performance.

We proposed a clustering-aided approach to selecting patient samples for better predictive performance. We improved the predictive performance in two ways: (1) we selected key risk factors as features for the training data set, and (2) we applied clustering-aided approaches to improve the quality of the patient set. Specifically, we reviewed major clinical risk factors for elderly falls in the literature. Then, we converted patients' clinical features and demographic features to a patient feature set. Next, we clustered the patient set into three independent clusters. Finally, we utilized clusters to train separate machine learning prediction models. We demonstrated that machine learning models can achieve higher performance when the patient set is clustered. We believe that our approach may be applied to make other diagnostic predictions in clinical practice.

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A. *Significance of Study*

Predicting the risk of falls has significant implications for their prevention. Physicians can suggest precautions for high-risk patients. Proactive alerts reduce the risk of serious injuries. In a broader context, the clustering algorithm can be adopted for other comparable machine learning–based predictions of diagnosis. Unsupervised learning can draw further attention to building a high-quality data set for prediction. The combination of supervised and unsupervised approaches demonstrates the potential for using our approach for other similar diagnosis-based prediction problems due to its accuracy.

B. *Related Work*

Falls are a leading cause of mortality and morbidity among older adults, accounting for 87% of all fractures among the elderly[3]. Research has identified several risk factors contributing to falls. According to a synopsis of the relevant evidence on fall factors [3], the risk factors associated with the development of falls can be categorized into extrinsic and intrinsic factors. Extrinsic factors refer to any factors that come from outside of an individual, including living environment (e.g., poor lighting and loose rugs) and footwear (e.g., high heels and barefoot). In contrast, intrinsic factors are person-specific; they are based on the characteristics of an individual reflected in EHRs. Most risk factors found in the literature review[3] were intrinsic and included a wide range of risk categories: demographic profile, lower extremity strength, vertigo and dizziness, vision, cognition, cardiovascular disease, medications, depression, gait, and balance caused by normal aging and pathological effects. Additionally, each risk category had several risk factors that, when co-existent, might increase the chances of falling. For instance, orthostatic hypotension, hypertension, and atrial fibrillation fall under the cardiovascular disease category. Gangavati et al. [7] found that older adults with systolic orthostatic hypotension and uncontrolled hypertension had a higher risk of falling (hazard ratio = 2.5, 95% confidence interval = 1.3, 5.0) than those with uncontrolled hypertension alone.

Elderly falls are not uncontrollable acts of fate. There are predictive patterns for them based on known risk factors and defined demographics. A study [8] has shown that the physiological changes associated with aging account for 72% of falls, whereas the other 18% are unpredictable and categorized as accidental because they are the result of environmental hazards. The cognitive and motor performance deficiencies are significantly associated with fall risk suggests that falls can be predicted through clinical assessments. Conventionally, the most accurate health monitoring occurs in a laboratory or hospital setting, but such hospital-based health monitoring is prohibitively expensive and not regularly undertaken[9]. The automatic fall detection approach, on the other hand, allows for the early detection of elderly individuals in danger of falling or the detection of those who have already fallen so that subsequent interventions can be made. This capability can reduce the incidence of initial and subsequent falls and mitigate physical and mental suffering.

Recent decades have seen a large body of research utilizing machine learning techniques for fall detection, with numerous attempts being made to tackle the problem from multiple perspectives. Such studies have included various classification techniques [10], [11], types of sensors [12], and specific feature engineering methodologies [13]. However, little is known about the effectiveness of utilizing a clustering-aided approach in fall detection. Clustering-aided classification typically refers to a supervised machine learning classification task that is incorporated with clustering techniques. Clustering is one of the pattern recognition techniques, the goal of which is to organize a collection of objects so that those in the same group (referred to as a cluster) are more similar than those in other groups (clusters) [14]. Clustering analysis identifies a latent structure within a data set by deciding which entities belong to which group. Typology identification, data exploration, hypothesis generation, and data reduction are all common use cases for cluster analysis, which combines comparable instances into homogenous classes for the purpose of organizing vast amounts of information and providing labels to facilitate information exchange and processing [15] In the healthcare domain, the application of clustering has been successfully implemented for better cost and care management, such as grouping patients who had similar changes in healthcare costs before and after treatment [15] and identifying subpopulations of complex patients for potential targeted care management within an integrated health maintenance organization [16].

Although clustering algorithm is an unsupervised machine learning technique, previous research [17] has suggested that they improve prediction accuracy when used to preprocess data. The utility of clustering in aiding classification tasks has also been demonstrated [18]. Clustering-assisted approaches or multiple models are not novel concepts; however, they have been mostly used for industrial tasks. There have been some attempts [19] to develop two machine learning models for each group of patients to predict inpatient lengths of stay and discharge destinations. The results revealed that the models could make predictions with a high accuracy when combining unsupervised and supervised learning. To investigate the effectiveness of the clustering-aided technique in elderly fall detection, we built a clustering-aided predictor that takes advantage of the group features found in existing patient profiles to maximize data utilization. To the best of our knowledge, this approach has not been used in previous fall predictions; hence, its integration is innovative.

II. METHODOLOGY

Figure 1 shows a graphical abstract of the study. We first selected risk factors from EHRs. A total of 24 risk factor features in our literature review showed potential association with elderly falls, including patients' demographics, clinical diagnoses, and medication records. Each risk factor was converted into a patient-level feature. Each feature indicated the occurrence of a specific diagnosis or procedure. Based on the selected features, we built a feature set that included 386,480 patients over 60 years of age. We then used the K-means algorithm to split the data set into three independent clusters. We compared each cluster's demographic and clinical features with those of the other clusters. Finally, we compared the performance of two types of machine learning models, with one type trained on a non-clustered feature set and the other models trained on a separate clustered feature set. All experiments were implemented using Python (3.8.4).

A. Building Feature Set

1) Data Source: We used EHRs from Froedtert Health Clinical Research Data Warehouse , which stores the records of 1.4 million unique patients who visited the facility. We acquired a data set from the CRDW based on the following criteria: (1) all patients were over 60 years old at the time of visiting the Froedtert Health facility, and (2) the dates of the patients' visits were between 2009/01/01 and 2021/05/31.

2) Feature Extraction: We first retrieved patients' falling history from diagnosis records. The patients' fall diagnosis was selected according to the International Classification of Diseases code. Several risk factors, notably demographic characteristics, clinical diagnoses, and medication histories, have been associated with elderly fall diagnoses. Each feature indicated whether a patient was diagnosed with a condition or prescribed a drug. The feature name lists are shown in Table 1.

3) Data Cleaning: Data anomalies are unavoidable. To clean the data, we applied several measures. First, we excluded data with missing categorical values. For continuous variables, we filled the missing values with a group median. To minimize the bias of large variations, we applied feature scaling to the entire feature set. Continuous variables were then rescaled using a feature scaling step to avoid a varied range of feature values. All features were normalized and rescaled to the [0, 1] range.

B. Data Processing: Clustering Feature Set

1) Unsupervised Clustering: We applied the K-means algorithm, which decomposes patient characteristics and divides patient sets into K clusters.

2) Using Inertia to Determine the Appropriate Number of Clusters: We examined inertia to evaluate the internal coherence of clusters. Inertia measures how well a data set is clustered by K-means and provides a graphical suggestion of the best number of clusters. We set the number of clusters to range from 2 to 7. To find the optimal K for a data set, we used the elbow method. We found the point from Figure 2 where the decrease in inertia began to slow down. This point was the optimal K for our data set.

C. Model Training and Evaluation

1) Re-Sampling for Data Imbalance Issues: After clustering, patient clusters showed imbalances in positive and negative cases. The imbalances might have had negative effects on machine learning model prediction. To reduce potential imbalance issues, we resampled some of the patients in a specific age range so that the histogram and median age of each cluster were similar.

2) Building Classifiers: We built two machine learning classifiers. We based one on a non-clustered data set, and the other on a clustered data set split into three clusters. For each data set, we adopted logistic regression and random forest algorithms to predict the occurrence of falls. Each patient was assigned a binary value to indicate previous fall events. A few direct dependent variables of falls were removed to avoid overfitting (ICD code: W00–W19, R26.*, Z91.81; 781.2).

3) Model Evaluation: We compared the performance of the clustering-aided approach with a naïve machine learning approach. The comparative analysis clearly showed the differences in predicting the accuracy of falls for the elderly group between clustered and non-clustered groups.

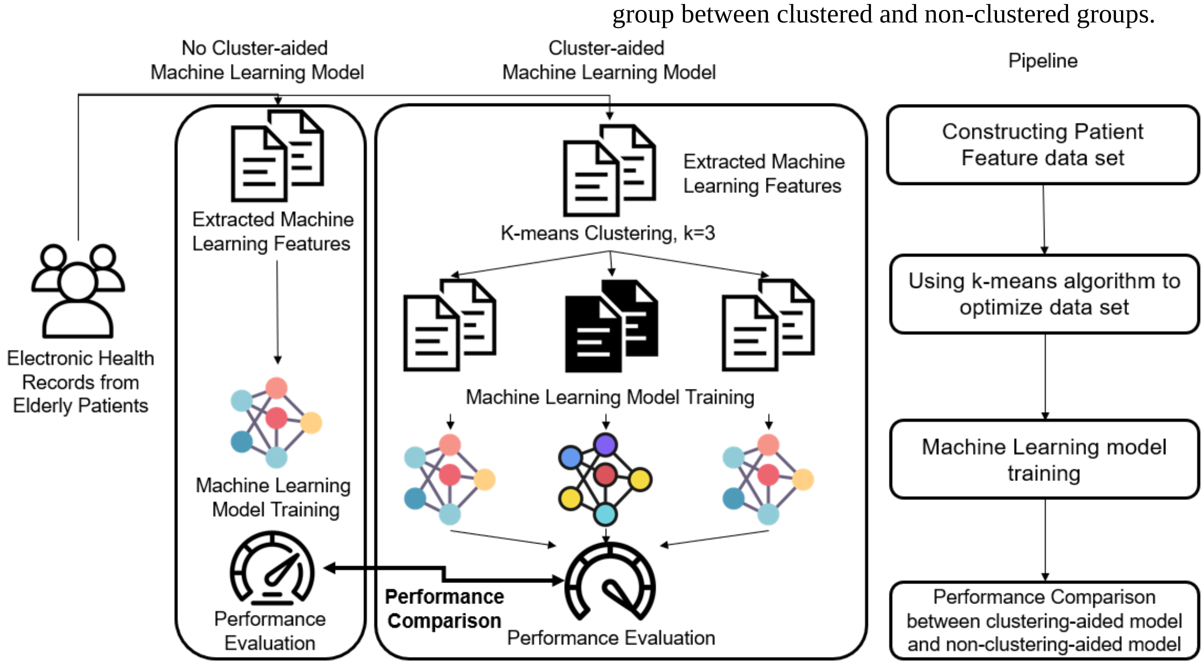

Fig. 1. Overview of Study. In the baseline model (left), we extracted key features from EHRs to form a training set, applied machine learning algorithms, and evaluated the model's performance. In the cluster-aided model (middle), we first applied the K-mean algorithm to partition the feature set into three distinct sets. We then applied machine learning to three clustered feature sets and calculated the final average performance for the three models. Finally, we compared the performance of the cluster-aided and non-cluster-aided machine learning models. Consequently, we verified the utility of K-means clustering to improve the model's performance.

III. Results

A. Overview of Patient Group and Feature Set

We acquired a set of 384,680 patients. The median age was 74.3 years. The median length of inpatient stay was 3.38 days. A total of 72.3% of the patients stayed in the hospital for less than three days. A total of 83% of the patients were White or Caucasian, and 10% of all patients were Black or African American. A total of 48,235 (12.5%) patients were diagnosed with falls. The most common risk factor for falls was hypertension, with which 198,058 (51.5%) patients were diagnosed. Other leading risk factors included cardiovascular diseases (12.0%), dizziness (12.0%), vision impairment (9.2%), hypotension (9.0%), hearing loss (8.8%), presbyopia (6.2%), macular degeneration (5.6%), dementia (4.6%), and depression (3.6%). The risk factors for common medication were as follows: anti-inflammatory drugs (23.9%), antidiabetic drugs (18.8%), antidepressants (18.7%), and cardiovascular medications (4.7%). Other demographic information, including age, gender, ethnicity, and patient length of stay, were also converted into a feature set.

B. Determining the Number of K-Means Clusters (K)

Selecting an appropriate number of clusters is key to achieving optimal separation, which may improve the performance of prediction. Figure 2 shows a line chart of how inertia value declines as the number of clusters increases. Figure 3 shows inertia values when the number of clusters ranges from 1 to 9. Using the elbow method, we determined that K = 3 was an appropriate number of clusters to minimize the variance and number of clusters.

C. Comparison of Clustered Patient Group Characteristics and Risk Factors

From Table 1, we analyzed the demographic and clinical characteristics of the different clusters. Cluster 2 was identified as a high-risk group. The differences between Cluster 2 and the baseline group were significant in all features, including the percentage of fall patients (64.0% versus 12.5%), median age (76.2 versus 74.3), length of stay in hospital (28.06 days versus 3.38 days), overall diagnostic record for a variety of fall-related conditions (28.0% versus 8.1%), and medication orders (55.3% versus 16.5%). Thus, the K-means algorithm successfully identified and clustered the high-risk group from the data set.

D. Machine Learning Prediction and Performances

We applied random forest and logistic regression models to clustered and non-clustered data sets. The logistic regression algorithm served as a fundamental statistical model for evaluating the performance of the machine learning classifier. We applied each algorithm to the baseline patient set (n = 386,480) and cluster-aided sets (three clusters, n = 169,993, 18,942, and 197,545, respectively). The performance of the cluster-aided set was weighted averaged and plotted in Figures 3 and 4. All evaluations utilized 10-fold cross-validation to ensure the stability of the performance.

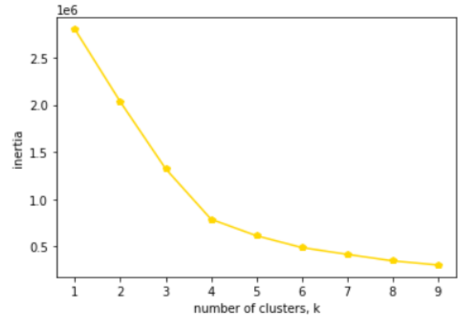

Fig. 2. Inertia Values When the Number of Clusters Ranges from 1 to 9. The data points when K = 3 and K = 4 form the "elbow" of the chart, with K = 3 achieving the most appropriate separation.

TABLE I. Comparison of Non-Clustered (Baseline) and Three Clustered Patient Groups

	Baseline Non-Clustered Count	Cluster 1 %	Cluster 2, %	Cluster 3, %
Total # of Patients	384,680	169,993	18,942	197,545
# of Fall Patients	48,235	15,171	12,127	20,937
% of Fall Patients	12.5%	8.9%	64.0%	10.6%
Median Age (Years)	74.3	73.6	76.2	74.8
Median length of stay	3.38	2.31	28.06	1.94
Male	177873	46%	169938	100%
Female	208552	54%	0	0%
White	318397	83%	140496	83%
Black	37598	10%	14995	9%
Asian	4015	1%	1735	1%
Other	8318	2%	3791	2%
Unknown	16352	4%	8976	5%
Hypertension	198058	51%	84863	50%
Gait and Balance	40071	10%	13722	8%
Vertigo	9637	3%	2544	1%
Vision	35351	9%	12152	7%
Dizziness	46171	12%	14525	9%
Dementia	17530	5%	5471	3%
Depression	14020	4%	3231	2%
Alzheimer's	8978	2%	2532	1%
Parkinson's	6919	2%	3573	2%
Dystonia	2155	1%	600	0%
Lack of Coordination	4675	1%	1610	1%
Cardiovascular disease	46316	12%	21317	13%
Hypotension	34802	9%	13119	8%
Macular Degeneration	21662	6%	7007	4%
Hearing Loss	33753	9%	13934	8%
Presbyopia	24019	6%	8510	5%
Diabetic Retinopathy	6102	2%	2274	1%
Alcohol Disorders	8137	2%	4564	3%
Antidepressants	71991	19%	22248	13%
Antidiabetic	72415	19%	32273	19%
Anti-Inflammatory	91834	24%	35080	21%
Med Cardiovascular	18046	5%	12757	8%

Figures 3 and 4 show the accuracy, AUROC, and F1 scores of machine learning predictions. The clustered sample performances were calculated based on the weighted average performance of each cluster. The F1 and AUROC scores clearly demonstrated that a cluster-aided model achieved a significantly higher fall prediction rate based on the feature set.

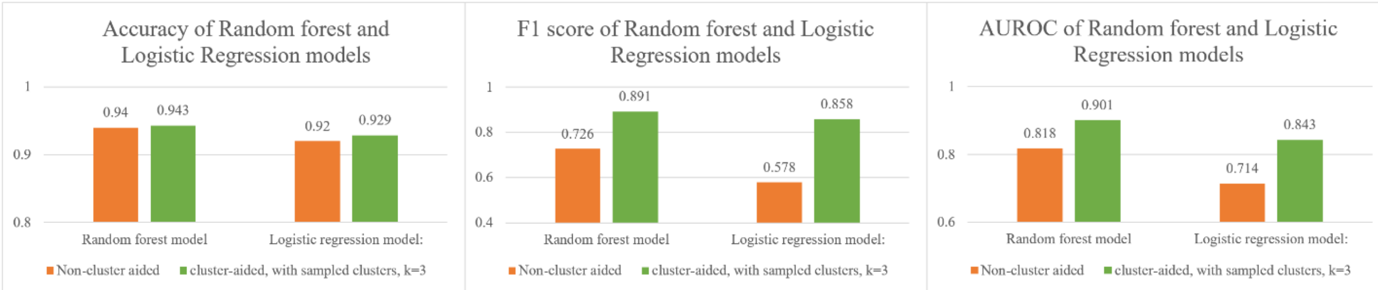

Fig. 3. Overall Performance of Random Forest and Logistic Regression Models

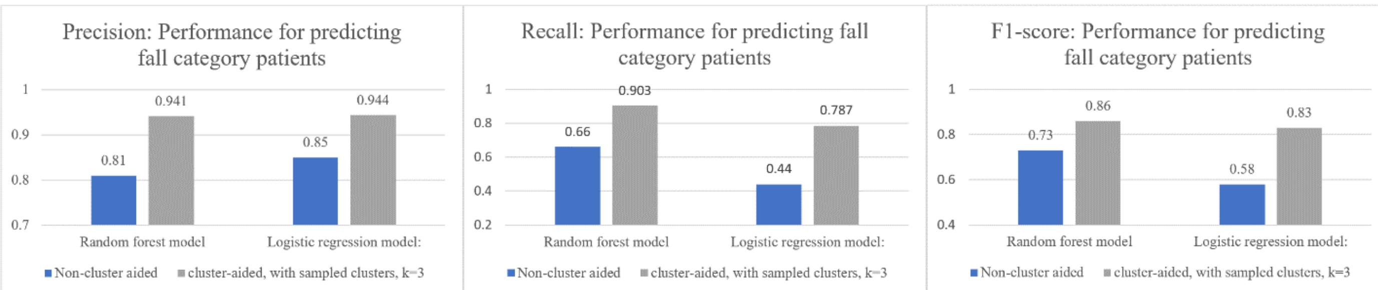

Fig. 4. Precision, Recall, and F1 Scores of Random Forest and Logistic Regression Models for Fall Diagnosis Prediction Showing Only Positive Results

IV. Discussion

This study focused on the utility of a clustering-aided approach to improving prediction performance. We collected a set of risk factor features related to elderly falls and built a feature set for 384,680 patients. A clustering-based approach identified a high-risk patient group from a three-cluster partition. The comparison between the non-clustered group and the high-risk group was conducted in two ways: (1) a comparison of patient characteristics and risk factors between the baseline group and the high-risk group, and (2) the comparison of machine learning models' performances when they were trained on a non-clustered patient group and three clustered patient groups. The results indicated that a clustering approach could aggregate patients into a group with a significantly higher percentage of risk factors for falling. Indeed, the clustering-aided high-risk group led to a high-quality data set for machine leaning prediction. Two machine learning algorithms training on clustering-aided data sets achieved significantly better performances in fall prediction.

A. *Interpretation of Data Set*

It is important to understand how the K-means approach successfully achieves a significantly higher performance in the model. We thought two factors contributed to the predictive performance: first, a large patient set ranging over the last 10 years), and second, several common risk factors, which are clinical indicators of falls for predictive tasks. Our patient diagnosis records investigation was well aligned with common risk factors for falls. These risk factors, including patients' demographics, clinical diagnoses, and medication records in the data set, could be used for decision-making model development. Using an integration of related risk factors, our model successfully predicted a fall event.

The percentage of patients with fall histories varied between the baseline group and the high-risk group (12.5% versus 64.0%), which allowed for balanced data for training in the high-risk group. A data set with balanced positive and negative labels usually results in a more unbiased prediction and avoids possible errors. Demographic differences, specifically age and length of stay, were also significant. Both unsupervised learning and supervised learning contributed to the results. The K-means clustering approach discovered the gap of the two groups and separated a small portion of the high-risk group. Machine learning algorithms utilized this gap to achieve a better prediction. Finally, the risk factor set strongly contributed to improving prediction performance because the difference in percentage values between clustered and non-clustered groups was also significant, which makes for a helpful feature set to improve machine learning prediction.

B. *Why Can the K-Means Approach Classify and Identify a High-Risk Group From Data Set?*

The K-means algorithm relied on patient profiles. These profiles included a combination of the patient's age, inpatient stay, demographic characteristics, medication records, and diagnosis records. Since we observed similar patterns in the patient set, K-means successfully placed patients into a high-risk group. The risk factor differences observed in Table 1 include a higher percentage of fall-diagnosed patients, a significantly higher age, a longer length of inpatient stay, and a higher percentage of clinical diagnoses and medications.

C. *Comparison of Prediction Algorithms*

We applied two algorithms to non-clustered and clustered sets. The aim was two-fold: (1) to compare the predictive performance of non-clustered and clustered models, and (2) to choose the best algorithm among logistic regression and random forest models. We discovered that the random forest model achieved the best performance. We believe that a decision tree–based structure naturally fits the character of patient sets, thus leading to a higher predictive performance than that of other algorithms.

D. Why Does the K-Means Approach Improve Performance?

Our results showed that the importance of selected features varied from one cluster of patients to another. Accordingly, the clustering-aided approach could make finer-grained predictions in patients who naturally share a common set of characteristics or experience similar outcomes. The clustering approach evaluated the initial risk according to clinical variables. K-means categorized the risk level from each patient's clinical and demographic records, which virtually indicated the risk of falls. Therefore, the internal variability for each subcluster was significantly smaller than that of the non-clustered patient set. Given that each cluster had different clinical risks, each machine learning model could be tailored to the feature set in the training progress. Since patients in a sub-group exhibited smaller differences between each other than those in the whole non-clustered group, a tailored model could make a finer prediction than a model fitting the entire non-clustered feature set. A cluster-aided approach could split a large feature set into a few smaller sets in which each model could adapt to a feature set to improve the predictive performance. In a clustering approach, a patient is assigned to certain clusters of similar demographic and clinical characteristics. Thus, each model could be adjusted according to its clinical characteristics to mitigate the overfitting issue.

E. Limitations and Future Work

This study has a few experimental limitations. First, the patients were clustered based on a data-driven approach without considering a clinical perspective. Furthermore, the selection of patient features from the EHRs did not include all the features related to fall diagnosis. A more careful selection of clinical features from a clinician's perspective could have improved the quality of the feature set and the predictive performance. Due to the limitations of computational power, we could not verify the model's performance in a complex neural net. We also evaluated the efficacy of a cluster-aided approach for other diagnoses and ensured generalizability of prediction models. Clinicians' evaluation will be included in our future work.

V. Conclusion

Building a patient set in machine learning can lead to accurate diagnosis prediction. Our experiment combined unsupervised and supervised learning, which demonstrated the significance of patient clustering. Specifically, we demonstrated that a clustering algorithm could identify patients who shared similar characteristics from clinical or demographic perspectives. The clustering resulted in a high-quality data set and supported the machine learning prediction of diagnosis. A clustering-aided approach can make finer-grained predictions for patients who naturally share a common set of characteristics or experienced similar outcomes. Thus, our approach provided more accurate predictions than non-clustering-based predictions. In a broader context, we believe that this study can be considered along with comparable machine learning healthcare problems.

References

[1] S. R. B. L. Shrivastava, P. S. Shrivastava, and J. Ramasamy, “Health-care of Elderly: Determinants, Needs and Services,” *Int. J. Prev. Med.*, vol. 4, no. 10, p. 1224, 2013, Accessed: Oct. 04, 2021. [Online]. Available: /pmc/articles/PMC3843313/.

[2] W. H. Organization, *WHO global report on falls prevention in older age*. 2008.

[3] A. F. Ambrose, G. Paul, and J. M. Hausdorff, “Risk factors for falls among older adults: A review of the literature,” *Maturitas*, vol. 75, no. 1, pp. 51–61, May 2013, doi: 10.1016/J.MATURITAS.2013.02.009.

[4] E. H. Shortliffe and J. J. Cimino, *Biomedical Informatics: Computer applications in health care and biomedicine*, 4th ed. Springer, 2014.

[5] S. B. Kotsiantis, I. Zaharakis, P. Pintelas, and others, “Supervised machine learning: A review of classification techniques,” *Emerg. Artif. Intell. Appl. Comput. Eng.*, vol. 160, no. 1, pp. 3–24, 2007.

[6] K. Shailaja, B. Seetharamulu, and M. A. Jabbar, “Machine Learning in Healthcare: A Review,” *Proc. 2nd Int. Conf. Electron. Commun. Aerosp. Technol. ICECA 2018*, pp. 910–914, Sep. 2018, doi: 10.1109/ICECA.2018.8474918.

[7] A. Gangavati *et al.*, “Hypertension, Orthostatic Hypotension, and the Risk of Falls in a Community-Dwelling Elderly Population: The Maintenance of Balance, Independent Living, Intellect, and Zest in the Elderly of Boston Study,” *J. Am. Geriatr. Soc.*, vol. 59, no. 3, pp. 383–389, Mar. 2011, doi: 10.1111/J.1532-5415.2011.03317.X.

[8] J. Hamm, A. G. Money, A. Atwal, and I. Paraskevopoulos, “Fall prevention intervention technologies: A conceptual framework and survey of the state of the art,” *J. Biomed. Inform.*, vol. 59, pp. 319–345, Feb. 2016, doi: 10.1016/J.JBI.2015.12.013.

[9] G. Forbes, S. Massie, and S. Craw, “Fall prediction using behavioural modelling from sensor data in smart homes,” *Artif. Intell. Rev.*, vol. 53, no. 2, pp. 1071–1091, Mar. 2019, doi: 10.1007/S10462-019-09687-7.

[10] N. Zerrouki, F. Harrou, A. Houacine, and Y. Sun, “Fall detection using supervised machine learning algorithms: A comparative study,” *Proc. 2016 8th Int. Conf. Model. Identif. Control. ICMIC 2016*, pp. 665–670, Jan. 2017, doi: 10.1109/ICMIC.2016.7804195.

[11] A. Núñez-Marcos, G. Azkune, and I. Arganda-Carreras, “Vision-based fall detection with convolutional neural networks,” *Wirel. Commun. Mob. Comput.*, vol. 2017, 2017, doi: 10.1155/2017/9474806.

[12] G. Mastorakis and D. Makris, “Fall detection system using Kinect's infrared sensor,” *J. Real-Time Image Process.*, vol. 9, no. 4, pp. 635–646, Mar. 2012, doi: 10.1007/S11554-012-0246-9.

[13] A. Ramachandran, A. Ramesh, and A. Karuppiah, “Evaluation of Feature Engineering on Wearable Sensor-based Fall Detection,” *Int. Conf. Inf. Netw.*, vol. 2020-January, pp. 110–114, Jan. 2020, doi: 10.1109/ICOIN48656.2020.9016479.

[14] E. Diday and J. C. Simon, “Clustering Analysis,” in *Digital Pattern Recognition*, Springer, Berlin, Heidelberg, 1976, pp. 47–94.

[15] M. Liao, Y. Li, F. Kianifard, E. Obi, and S. Arcona, “Cluster analysis and its application to healthcare claims data: a study of end-stage renal disease patients who initiated hemodialysis,” *BMC Nephrol.*, vol. 17, no. 1, pp. 1–14, Mar. 2016, doi: 10.1186/S12882-016-0238-2.

[16] S. R. Newcomer, J. F. Steiner, and E. A. Bayliss, “Identifying subgroups of complex patients with cluster analysis,” *Am. J. Manag. Care*, vol. 17, no. 8, pp. e324-32, Aug. 2011.

[17] S. Trivedi, Z. A. Pardos, G. N. Sárközy, and N. T. Heffernan, “Spectral clustering in educational data mining,” in *EDM 2011 - Proceedings of the 4th International Conference on Educational Data Mining*, 2011, pp. 129–138.

[18] S. Trivedi, Z. A. Pardos, and N. T. Heffernan, “The Utility of Clustering in Prediction Tasks,” Sep. 2015, Accessed: Oct. 04, 2021. [Online]. Available: https://arxiv.org/abs/1509.06163v1.

[19] M. Elbattah and O. Molloy, “Clustering-aided approach for predicting patient outcomes with application to elderly healthcare in Ireland,” in *AAAI Workshop - Technical Report*, 2017, vol. WS-17-01-, pp. 533–541, Accessed: Oct. 04, 2021. [Online]. Available: https://www.aaai.org/ocs/index.php/WS/AAAIW17/paper/viewPaper/15188.