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Oldest Adults Daily Living Activities Detection using Machine Learning

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ABSTRACT

This research focuses on accurately recognising and monitoring Activities of Daily Living (ADLs) among older adults, with a specific emphasis on individuals with dementia. The study aims to evaluate and compare different machine learning models to identify the most effective approach for ADL classification. Models such as Artificial Neural Network (ANN), Random Forest (RF), Decision Tree (DT), Multinomial NB, and Logisticn Regression (LR) was tested on a dataset containing ADL features. The results revealed that the RF and DT models achieved the highest accuracy of 95.61% in classifying ADLs. These models demonstrated their ability to capture complex patterns in ADL data, making them promising candidates for ADL recognition and monitoring, especially for older adults with dementia.

اكتشاف أنشطة الحياة اليومية لكبار السن باستخدام التعلم الآلي

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الكلمات المفتاحية
أنشطة الحياة اليومية
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التعلم العميق
الغابة العشوائية
شجرة القرار

الملخص

تركز هذه الدراسة على التعرف بدقة على أنشطة الحياة اليومية ومراقبتها بين كبار السن، مع التركيز بشكل خاص على الأفراد المصابين بالخرف. تهدف الدراسة إلى تقييم ومقارنة نماذج التعلم الآلي المختلفة لتحديد النهج الأكثر فعالية لتصنيف أنشطة الحياة اليومية. تم اختبار نماذج مثل الشبكة العصبية الاصطناعية (ANN) والغابة العشوائية (RF) وشجرة القرار (DT) وNB متعدد الحدود والانحدار اللوجستي (LR) على مجموعة بيانات تحتوي على ميزات أنشطة الحياة اليومية. كشفت النتائج أن نموذجي RF وDT حققا أعلى دقة بنسبة 95.61٪ في تصنيف أنشطة الحياة اليومية. أثبتت هذه النماذج قدرتها على التقاط الأنماط المعقدة في بيانات أنشطة الحياة اليومية، مما يجعلها مرشحة واعدة للتعرف على أنشطة الحياة اليومية ومراقبتها، وخاصة لكبار السن المصابين بالخرف.

1. Introduction

The world is experiencing a profound demographic shift with a rapid increase in the ageing population. Projections indicate that by the year 2030, approximately 19% of the global population will fall within the age bracket of 74 to 84 years, with nearly half of those over 84 likely to be affected by dementia [20]. The year 2050 will witness over 1.92 billion elderly individuals worldwide [8]. This demographic transition poses unique challenges and opportunities, particularly concerning the well-being and care of the ageing population. Encouraging older adults to maintain independent living in their homes for as long as possible has become a pivotal objective. Research advocates for the benefits of independent living, enhancing the quality of life for seniors and alleviating financial stress [8]. Preserving the independence of older adults necessitates continuous observation and monitoring of their Activities of Daily Living (ADLs).

Identifying anomalies in ADLs, such as irregular exits from the house or detrimental behavioural patterns, can serve as vital indicators of underlying health issues, especially among individuals with dementia [14], [16]. Dementia, a multifaceted disorder impairing physical, mental, and cognitive functions, presents unique challenges for older adults. Those grappling with cognitive impairment often experience reduced independence in everyday activities, necessitating the support of caregivers. Timely detection of dementia and other mental illnesses is pivotal for early intervention and effective care. Surprisingly, approximately 75% of cases remain undiagnosed

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during their early stages [3], underscoring the urgent need for efficient monitoring and diagnostic tools.

In response to the ageing population's needs, efforts have intensified to foster "active and independent ageing". Such initiatives aim to provide the necessary support, including medical assistance and monitoring services, to enable older adults to lead fulfilling lives in their preferred environments. Among the fundamental components aiding in assessing an individual's well-being is ADL. Healthcare professionals rely on ADLs to evaluate patients' functional status, independence, and overall health [19]. Analysing trends in various ADLs offers a comprehensive understanding of an individual's daily activities and interactions with their surroundings, providing valuable insights to caregivers for tailored care and support.

Despite the significance of ADL monitoring, a critical gap persists in accurately recognising and monitoring the ADLs of oldest adults, particularly those with dementia. This issue can lead to inadequate care and diminished quality of life for this vulnerable population. Therefore, the primary focus of this research is to investigate methods for precise recognition and monitoring of ADLs in older adults by implementing a simple sensor network in their homes. By developing effective prediction models, this research seeks to detect progressive changes in ADL behaviour and provide caregivers with valuable insights to identify trends and abnormalities promptly.

This research aims to promote independent living for the oldest adults, especially those with dementia, and enhance their overall quality of life. By developing non-intrusive technology to monitor the behaviour and identify abnormal activities, we aim to reduce the need for institutional care, enabling the oldest adults to enjoy an extended period of independent living. This research holds significant implications in economic, social, and technological spheres. By curbing healthcare costs associated with institutional care, resources can be redirected to other critical areas, fostering societal wellbeing. Moreover, supporting independent living can nurture social connections and reduce isolation among the oldest adults, positively impacting communities. This thesis report endeavours to address the existing gaps in ADL monitoring for the oldest adults, particularly those facing dementia. By developing prediction models and non-intrusive sensor networks, we aim to contribute to policy development, technological advancements, and the overall well-being of the elderly population. Accurate recognition and monitoring of ADLs hold the potential to empower caregivers and policy makers with invaluable tools to promote independent living and health for our senior citizens.

This paper is structured as follows: in Section II some previous works are introduced; in Section III the proposed framework of this research is presented followed by the implementation of the methodology in Section VI. The validation of the results obtained and the conclusions are presented in Sections VII and VIII respectively.

2. Related Work

Monitoring human behaviour in smart environments is a challenging yet essential task, as it enables us to understand individuals' activities and well-being. Implementing a network of sensors and communication equipment in these environments allows continuous monitoring of participants, providing valuable insights into their behavioural changes over time. Several smart environment projects have been developed to support independent living for humans [13], [16]. Smart homes offer a cost-effective alternative to nursing homes, providing long-term monitoring to detect potential health concerns.

These environments can recognise changes in occupants' behaviour, diet, daily tasks, or health, alerting caregivers and family members to any significant deviations. Smart environments utilise human behaviour recognition to monitor activities, ensuring prompt alerts in case of abnormalities [6]. Ambient Intelligence (AmI) is a multidisciplinary approach to enhance interactions between environments and individuals. By integrating technology such as sensors and interconnected devices, AmI enables intelligent decision-making to benefit users based on real-time data and historical patterns. AmI systems offer flexibility, adaptation, and anticipation, making them ideal for supporting independent living and enriching human lives [5], [9].

Modelling human behaviour is complex due to the nonrandom nature of human actions and the diverse combination of rational decision-making and emotional responses. Traditional approaches, like the brain as a computer metaphor, have their limitations. Neural network-based cognition modelling is promising, but the challenges of building such systems hinder steady progress [12], [15].

Human behaviour modelling is crucial in constructing a safe environment for individuals, especially oldest adults. Hidden Markov Models and transfer learning have shown promise in detecting abnormal behaviour, supporting independent living, and assisting individuals in daily life. Synthetic data generation using Recursive Auto-Encoders is useful for cases with limited labelled training data [4], [17], [18].

Activities of daily living (ADLs) indicate behavioural variations and health changes. Monitoring multiple activities and analysing trends can help identify human behavioural evolution. Techniques like Deep 1D-CNN, Bi-LSTM neural networks, and Recurrent Neural Networks have shown high accuracy in activity recognition. Balancing privacy concerns, non-invasive motion sensor arrays and Internet of Things (IoT) systems can monitor activities without invading privacy [1], [10], [11].

The review highlights the potential of Ambient Intelligence in monitoring human behaviour in smart environments, promoting independent living and improving overall well-being. However, modelling human behaviour remains challenging due to its non-random and emotionally driven nature. Applying deep learning models, transfer learning, and non-invasive sensing technologies offer promising solutions to enhance daily activity monitoring and anomaly detection.

3. THE PROPOSED FRAMEWORK

The proposed anomaly detection approach involves several steps, as shown in Figure 1. First, a real-world dataset is gathered. Next, the input data is preprocessed using various methods to improve accuracy. Then, five models are downloaded from the Keras class. These steps are intended to enable the accurate detection of an anomaly.

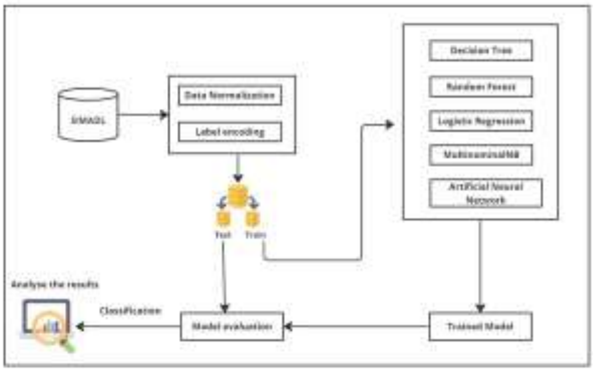

Fig. 1. Proposed Anomaly Detection Approach.

4. DATASET DESCRIPTION

SIMADL: Simulated activities of the daily living dataset are one of the most commonly used in the field of monitoring ADLs, generated by OpenSHS [7], an open-source simulation tool that offered the flexibility needed to generate residents' data for the classification of ADLs. For instance, it is used in studies to identify the activities of the daily living of individuals using machine learning and deep learning techniques. This set is used to train machine learning systems to accurately recognize and classify daily activities. In addition, used in studies to improve the quality of life of the elderly and people with disabilities, as this group is used to develop applications and devices that help these individuals to perform their life activities better. In general, is a powerful and unique dataset in the field of intelligence analysis of daily living activities, used in various studies to improve the quality of life of individuals [2]. However, it contains 31 columns. Figure 2 shows the distribution of the class labels. The features are the names of various objects and devices in a house or apartment. These features could be used as input variables for a machine-learning model designed to predict or control the state of these objects and devices. The activity labels that we decided to include in this dataset are sleep, eat, personal, work, leisure, and others. The anomaly detection dataset includes an additional label anomaly.

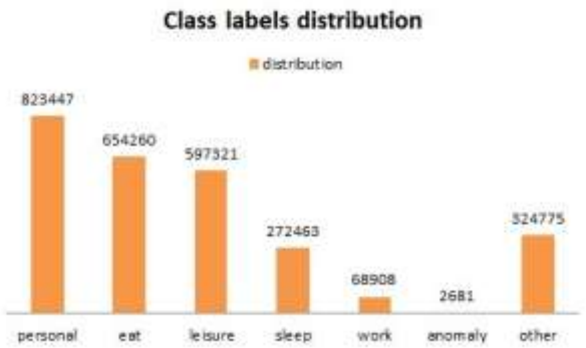

Fig. 2. Class label distribution.

5. DATA PREPROCESSING

A. Data normalisation

Data normalisation is a pivotal step in preprocessing, especially for machine learning applications. By scaling the data, we aim to set a standard where the mean is zero and the standard deviation is one. The main rationale behind this is to level the playing field for all the features. Differing scales among features can inadvertently give more weight to features with larger scales. This can hamper a model's performance, leading to biases in predictions. Therefore, normalisation can markedly improve a machine learning model's accuracy and performance. Among the techniques employed for this task, the standard-scaler method is frequently utilized, as it proves effective in adjusting data distributions and scaling.

B. Label Encoding

Within the broad spectrum of machine learning, the transition from categorical labels particularly those presented as strings to a more digestible numerical format is of paramount importance. The rationale behind this transformation is rooted in the operational characteristics of numerous machine learning algorithms. These algorithms are inherently designed to function more optimally with numerical data, streamlining their processes and enhancing their predictive accuracy. To break down this conversion process, one can envisage the various labels that might be used to describe the daily activities of senior citizens. An activity that is categorized as "personal" would be numerically represented as zero. In a similar fashion, the activity "eat" translates to one, while "leisure" corresponds to the number two. This systematic encoding continues to map each unique label to a distinct integer. As outlined in Table I, this structured approach is pivotal in ensuring that the data fed into machine learning models is both coherent and optimized for processing.

TABLE I DATASET LABELS ENCODING.

String labels	Integer labels
Personal	0
Eat	1
Leisure	2
Other	3
Sleep	4
Work	5
Anomaly	6

6. THE IMPLEMENTED MODELS

Each of these models has its strengths and weaknesses, and the choice of which model to use for a particular problem will depend on the specific characteristics of the dataset and the desired performance. The DT model is a simple and interpretable model that can be used for both classification and regression tasks. The RF model is an ensemble of multiple decision trees, which can improve the performance and robustness of the model compared to a single decision tree. The logistic regression model is a simple and interpretable model that can be used for binary classification tasks. Multinomial Naive Bayes is a classification algorithm based on the popular Naive Bayes algorithm. Finally, the artificial neural network is a powerful model that can learn to make predictions based on complex data.

A. Machine learning models implementation

Figure 3 illustrates the implementation of the proposed machine learning classifiers using the Sklearn library in Python. The classifiers include Decision Tree (DT), Random Forest (RF), Logistic Regression, and Multinomial Naive Bayes. These classifiers are trained on the preprocessed dataset and are used to classify human behaviour. The performance of these classifiers is evaluated and compared in the next chapter.

Fig. 3. The implementation of the proposed machine learning classifiers.

- Random Forest: a renowned ensemble learning method, has been deployed for the classification of Older Adults' Daily Living Activities. This methodology constructs multiple decision trees during training and outputs the mode of the classes for classification. It's especially advantageous for this application given its ability to handle high dimensional data and its inherent capability to manage non-linear decision boundaries. For the Older Adults' Daily Living Activities Detection, the categories under consideration are "personal", "eat", "leisure", "other", "sleep", "work", and "anomaly". Random Forest's capability to rank feature importance also provides insights into which aspects of the data are most indicative of a given activity, offering a holistic approach to understanding and detecting daily activities of older adults.
  - Multinomial Naive Bayes (NB) classifier: is rooted in applying Bayes' theorem with the assumption of independence between every pair of features. This architecture is particularly apt for datasets where features represent discrete counts or frequencies, making it a natural fit for text classification problems or any scenario with discrete data. In the context of Older Adults' Daily Living Activities Detection, the Multinomial NB provides an efficient and probabilistic approach to categorize activities based on the likelihood of observed patterns. Its simplicity, coupled with its effectiveness in high-dimensional datasets, allows for rapid classification of activities such as "personal", "eat", "leisure", "other", "sleep", "work", and "anomaly".
- Logistic Regression: is a statistical method tailored for binary or multinomial classification tasks, operating by estimating the probability that a given instance belongs to a particular category. In the framework of Older Adults' Daily Living Activities Detection, Logistic Regression makes use of a logistic function to squeeze the output of a linear equation between zero and one. This outcome can then be interpreted as the likelihood of an activity falling into one of the designated categories such as "personal", "eat", "leisure", "other", "sleep", "work", and "anomaly". Its strength lies in its simplicity, interpretability, and efficacy in scenarios where relationships are roughly linear. Furthermore, the coefficients in the logistic regression model offer insights into the importance and influence of each feature on the activity classification.
- Decision Tree architecture: offers a flowchart-like structure where each internal node represents a decision on an attribute, each branch signifies an outcome of that decision, and each leaf node holds a class label. Within the scope of Older Adults' Daily Living Activities Detection, the Decision Tree classifier assesses the features and recursively splits the data based on the feature that provides the maximum information gain or reduction in entropy. The beauty of this method lies in its visual interpretability and straightforward logic. Activities like "personal", "eat", "leisure", "other", "sleep", "work", and "anomaly" can be classified based on a hierarchy of decisions that best segregate the data. This approach not only provides a clear insight into the decision-making process but also ensures an intuitive understanding of the significance of each feature in activity classification.

B. Deep Learning model implementation

ANN is a sequential model with several layers, including dense, dropout, and activation layers. The first layer is dense with 64 units, meaning it will have 64 weights and biases. This layer also specifies the input shape, which is the shape of the input data. The next layer is also a dense layer with 64 units, and the third layer is a dense layer with 64 units and a ReLU activation function. The ReLU activation function is a common choice in deep learning models, as it helps to improve the model's performance by introducing nonlinearity. After the third layer, there is a dropout layer with a specified dropout rate. This layer randomly drops out a fraction of the inputs to the layer, which helps to prevent overfitting and improve the generalisation of the model. The next layer is a flattened layer, which reshapes the input data from a 3dimensional tensor to a 1-dimensional vector. This procedure is necessary because the next layer, a dense layer with 64 units and a ReLU activation function, expects a 1-dimensional input. After the dense layer, another dropout layer has the specified dropout rate. Finally, the model has a dense output layer with seven units and a softmax activation function. The softmax activation function is commonly used in classification tasks, as it outputs probabilities for each class. The model summary is then printed, which provides information about the model's architecture and the number of parameters in each layer, as illustrated in Figure 4.

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_19 (Dense)            (None, 29, 64)            128

 dense_20 (Dense)            (None, 29, 64)            4160

 dense_21 (Dense)            (None, 29, 64)            4160

 dropout_23 (Dropout)        (None, 29, 64)            0

 flatten_6 (Flatten)         (None, 1856)              0

 dense_22 (Dense)            (None, 64)                118848

 dropout_24 (Dropout)        (None, 64)                0

 dense_23 (Dense)            (None, 7)                 455

 activation_8 (Activation)   (None, 7)                 0

=================================================================
Total params: 127,751
Trainable params: 127,751
Non-trainable params: 0
_________________________________________________________________
```

Fig. 4. ANN model.

7. THE RESULTS

The classification report and confusion matrix obtained from the Python classification-report() function is used to evaluate the implemented models' performance. These tools calculate metrics using TP, TN, FP, and FN values. We also use training accuracy and loss curves to visualise the model's performance. These tools can help them understand how well the model predicts the classes in the dataset.

A. Artificial Neural Network Results

1) ANN model Compilation, Training, and Prediction: The ANN has three stages which are Compilation, Training and Prediction as follow:

1) Model Compilation The "compile" function configures the ANN model for training by specifying the loss function, optimizer, and metrics. The loss function, "sparse categorical cross-entropy", evaluates the model's performance during training for classification tasks with mutually exclusive classes. The optimizer, "Adamax", updates the model's weights based on computed gradients. The evaluation metric, "accuracy", measures the percentage of correctly classified examples. By using sparse categorical cross-entropy, Adamax optimizer, and accuracy metric, the model is prepared for training.
2) Model Training The "fit" function trains the model using the provided dataset, taking input features (X-train) and corresponding labels (Y-train). The batch size determines the number of examples processed before weight updates. For instance, a batch size of 500 processes 500 examples at a time. The number of epochs defines how many times the model goes through the entire training dataset. Each epoch represents a pass through the entire dataset. Additionally, validation data (X-test and Y-test) is used to evaluate the model's performance after each epoch, helping monitor progress and identify overfitting. This code trains the model for ten epochs, with a batch size of 500, and evaluates performance on the validation data.
3) Prediction After training, the "predict" function utilizes the trained model to generate predictions for the input data, specifically X-test. It returns an array of predictions, with each element corresponding to an example in the input data. By using the "predict" function, the model can provide predictions based on the trained weights.

However, Figure 5 illustrates the Model compilation, training and prediction.

```
model.compile(loss="sparse_categorical_crossentropy",
              optimizer='adamax',metrics=['accuracy'])
model_history=model.fit(X_train, y_train, batch_size=500,
                        epochs=10, validation_data=(X_test, y_test))
y_pred_test = model.predict(X_test).argmax(axis=1)
```

Fig. 5. Model compilation, training and prediction.

2) ANN model results: The provided metrics offer a detailed evaluation of the model's performance for each class in a multi-class classification problem. The labels for the classes are as follows: Personal, Heat, Leisure, Other, Sleep, Work, and Anomaly. The metrics include precision, recall, F1-score, and support.

Starting with the Personal class, the precision is calculated to be 0.96, indicating that 96% of instances predicted as Personal were correct. The recall value of 0.95 implies that 95% of actual Personal instances were correctly identified by the model. The F1-score, which combines precision and recall into a single metric, is 0.96. The support value for the Personal class is 246,860, representing the number of instances belonging to this class.

Moving on to the Heat class, the precision is measured at 0.98, indicating a high level of accuracy in predicting Heat. The recall value is 0.95, meaning that 95% of actual Heat instances were correctly classified by the model. The F1score for Heat is 0.96, indicating a balanced performance between precision and recall. The support value for Heat is 196,544. For the Leisure class, the precision is determined to be 0.97, reflecting a high accuracy in predicting Leisure. The recall value is 0.97, indicating that 97% of actual Leisure instances were correctly identified by the model. The F1-score for Leisure is 0.97, representing an overall good performance. The support value for Leisure is 178,899.

The Other class demonstrates a precision of 0.89, implying an 89% accuracy in predicting Other. The recall value is 0.99, indicating that 99% of actual Other instances were correctly classified. The F1-score for Other is 0.94, suggesting a relatively good balance between precision and recall. The support value for Other is 97,588.

Regarding the Sleep class, the precision value is 0.93, representing a 93% accuracy in predicting Sleep. The recall value is 0.94, indicating that 94% of actual Sleep instances were correctly identified by the model. The F1-score for Sleep is 0.93, indicating a good overall performance. The support value for Sleep is 81,777. Moving to the Work class, the precision is determined to be 0.97, indicating a high level of accuracy of 97% in predicting Work. The recall value is 0.91, meaning that 91% of actual Work instances were correctly classified by the model. The F1-score for Work is 0.94, suggesting a good balance between precision and recall. The support value for Work is 20,662.

Finally, for the Anomaly class, the precision value is 0.60, implying a 60% accuracy in predicting Anomaly. The recall value is 0.81, indicating that 81% of actual Anomaly instances were correctly identified by the model. The F1-score for Anomaly is 0.69, suggesting a moderate performance. The support value for Anomaly is 827. Considering all the classes, the accuracy of the model is calculated to be 95.52%. These metrics provide a comprehensive assessment of the model's performance for each class, enabling further analysis and evaluation. The classification report illustrated in Figure 6 shows that the dataset has seven classes, and the model's performance is evaluated on a test set.

Other important insights come from interpreting the confusion matrix in Figure 7. For the "Heat" class, the confusion matrix shows that 185,929 instances were correctly classified as Heat. However, there were 2,378 instances incorrectly classified as Heat when they belonged to other classes. Furthermore, 4,069 instances were mistakenly classified as other classes when they were actually part of the Heat class. On the positive side, 3,181 instances were correctly classified as other

	precision	recall	f1-score	support
0	0.96	0.95	0.96	246860
1	0.98	0.95	0.96	196544
2	0.97	0.97	0.97	178899
3	0.89	0.99	0.94	97588
4	0.93	0.94	0.93	81777
5	0.97	0.91	0.94	20662
6	0.60	0.81	0.69	827

Fig. 6. ANN classification report.

classes.

For the "Leisure" class, the confusion matrix indicates that 173,845 instances were correctly classified as Leisure. However, there were 747 instances incorrectly classified as Leisure when they belonged to other classes. Moreover, 2,758 instances were mistakenly classified as other classes when they were actually part of the Leisure class. On the positive side, 879 instances were correctly classified as other classes.

Regarding the "Other" class, the confusion matrix shows that 96,587 instances were correctly classified as Other. There were 990 instances incorrectly classified as Other when they belonged to other classes. Surprisingly, only 11 instances were mistakenly classified as other classes when they were actually part of the other class. However, there were no instances correctly classified as other classes.

Examining the "Sleep" class, the confusion matrix reveals that 76,877 instances were correctly classified as Sleep. There were 4,195 instances incorrectly classified as Sleep when they belonged to other classes. Additionally, 137 instances were mistakenly classified as other classes when they were actually part of the Sleep class. On the positive side, 54 instances were correctly classified as other classes.

In the case of the "Work" class, the confusion matrix indicates that 18,902 instances were correctly classified as Work. However, there were 247 instances incorrectly classified as Work when they belonged to other classes. Additionally, 52 instances were mistakenly classified as other classes when they were actually part of the Work class. Similar to the "Other" class, there were no instances correctly classified as other classes.

Finally, for the "Anomaly" class, the confusion matrix shows that 667 instances were correctly classified as Anomaly. There were 5 instances incorrectly classified as Anomaly when they belonged to other classes. Moreover, 7 instances were mistakenly classified as other classes when they were actually part of the Anomaly class. On the positive side.

The training was performed for 10 epochs, and the validation accuracy and loss were monitored after each epoch. In the given results in Figure 8, the training accuracy steadily increased from 94.43% in the first epoch to 95.46% in the final epoch. This indicates that the model became progressively better at predicting the correct class labels as the training progressed. Similarly, the validation accuracy improved from 95.34% in the first epoch to 95.52% in the tenth epoch. The

	precision	recall	f1-score	support
0	0.96	0.95	0.96	246860
1	0.98	0.95	0.96	196544
2	0.97	0.97	0.97	178899
3	0.89	0.99	0.94	97588
4	0.93	0.94	0.93	81777
5	0.97	0.91	0.94	20662
6	0.60	0.81	0.69	827

Fig. 7. ANN confusion matrix.

loss refers to the error or mismatch between the predicted and actual class labels. A lower loss value indicates that the model's predictions align more closely with the true labels. In Figure 9, the training loss gradually decreased from 0.1654 in the first epoch to 0.1235 in the final epoch. This signifies that the model's predictions became more accurate as the training proceeded. The validation loss followed a similar pattern, decreasing from 0.1266 in the first epoch to 0.1192 in the tenth epoch.

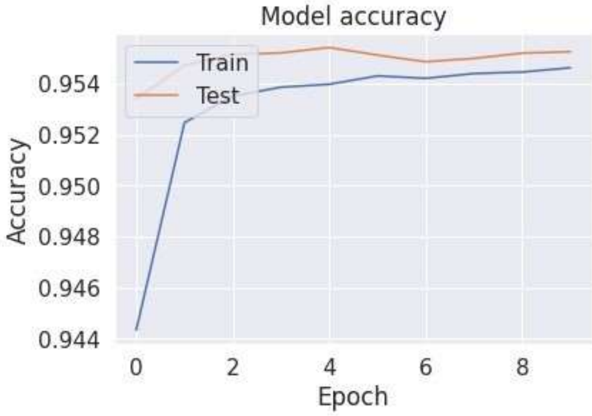

Fig. 8. The ANN model accuracy.

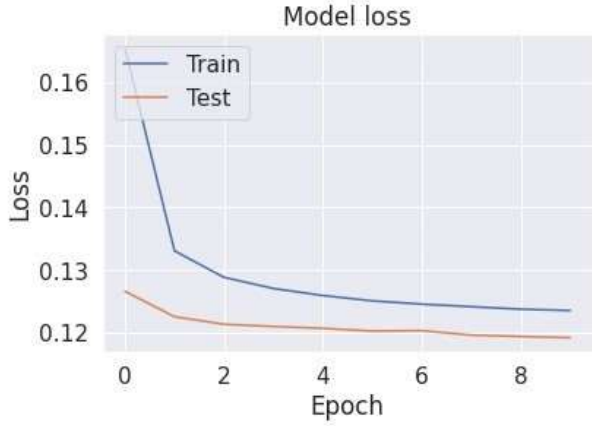

Fig. 9. The ANN model loss.

B. Decision Tree Results

The provided confusion matrix in Figure represents the classification results of a DT model for a multi-class classification problem. Starting with the Personal class, the confusion matrix indicates that 647 instances were correctly classified as Personal. However, there was 1 instance mistakenly classified as Personal when it belonged to another class. Additionally, 138 instances were incorrectly classified as other classes when they actually belonged to the Personal class. On the positive side, 4 instances were correctly classified as other classes.

Moving on to the Eat class, the confusion matrix shows that 185,800 instances were correctly classified as Eat. However, there were 261 instances incorrectly classified as Eat when they belonged to other classes. Furthermore, 3,619 instances were mistakenly classified as other classes when they actually belonged to the Eat class. On the positive side, 6,664 instances were correctly classified as other classes.

Regarding the Leisure Class, the confusion matrix indicates that 173,619 instances were correctly classified as Leisure. There were 3,099 instances incorrectly classified as Leisure when they belonged to other classes. Moreover, 974 instances were mistakenly classified as other classes when they actually belonged to the Leisure class. On the positive side, 729 instances were correctly classified as other classes.

For the Other class, the confusion matrix reveals that 96,521 instances were correctly classified as Other. There were 970 instances incorrectly classified as Other when they belonged to other classes. Surprisingly, only 12 instances were mistakenly classified as other classes when they belonged to the Other class. However, there were no instances correctly classified as other classes.

Examining the Sleep class (label 4), the confusion matrix shows that 234,111 instances were correctly classified as Sleep. There were 4,215 instances incorrectly classified as Sleep when they belonged to other classes. Additionally, 6,457 instances were mistakenly classified as other classes when they actually belonged to the Sleep class. On the positive side, 4,284 instances were correctly classified as other classes.

In the case of the Work class, the confusion matrix indicates that 77,318 instances were correctly classified as Work. There were 118 instances incorrectly classified as Work when they belonged to other classes. Moreover, 62 instances were mistakenly classified as other classes when they actually belonged to the Work class. On the positive side, 66 instances were correctly classified as other classes.

Finally, for the Anomaly class, the confusion matrix shows that 19,045 instances were correctly classified as Anomaly. There were 38 instances incorrectly classified as Anomaly when they belonged to other classes. Furthermore, 552 instances were mistakenly classified as other classes when they actually belonged to the Anomaly class. On the positive side, 18,888 instances were correctly classified as other classes. Figure 10 shows the confusion matrix results.

The provided metrics offer a comprehensive evaluation of a model's performance in a multi-class classification problem.

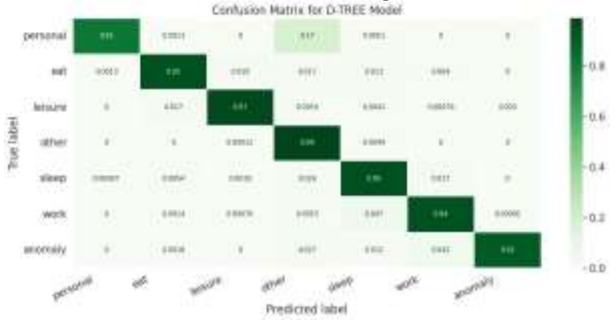

Fig. 10. Decision Tree confusion matrix.

They provide valuable insights into precision, recall, and F1score for each class, along with the support value representing the number of instances in each class.

Starting with the Anomaly class, the precision of 0.58 indicates that 58% of instances predicted as Anomaly were actually correct. The recall of 0.82 suggests that the model identified 82% of the actual Anomaly instances correctly. The F1-score of 0.68 represents a balance between precision and recall for the Anomaly class, considering their harmonic mean. The support value of 790 signifies the number of instances belonging to the Anomaly class in the dataset.

Moving on to the Eat class, the precision of 0.98 highlights a high level of accuracy in predicting Eat. The recall value of 0.95 indicates that 95% of the actual Eat instances were correctly classified by the model. The F1-score of 0.96 demonstrates the overall performance of the model in terms of precision and recall for the Eat class. The support value of 196,344 denotes the number of instances in the Eat class.

For the Leisure class, the precision of 0.98 showcases a high accuracy in predicting Leisure. The recall value of 0.97 suggests that 97% of the actual Leisure instances were correctly identified by the model. The F1-score of 0.97 represents a harmonious balance between precision and recall for the Leisure class. The support value of 179,101 indicates the number of instances in the Leisure class.

Moving to the Other class, the precision of 0.89 indicates an 89% accuracy in predicting Other. The recall value of 0.99 signifies that 99% of the actual Other instances were correctly classified by the model. The F1-score of 0.94 represents a relatively balanced performance between precision and recall for the Other class. The support value of 97,503 indicates the number of instances in the Other class.

Examining the Personal class, the precision of 0.97 indicates a high level of accuracy, with 97% of instances predicted as Personal being correct. The recall value of 0.95 suggests that 95% of the actual Personal instances were correctly identified by the model. The F1-score of 0.96 represents a good overall performance in terms of precision and recall for the Personal class. The support value of 246,838 indicates the number of instances in the Personal class.

Looking at the Sleep class, the precision of 0.93 demonstrates a 93% accuracy in predicting Sleep. The recall value of 0.94 suggests that 94% of the actual Sleep instances were correctly classified by the model. The F1-score of 0.94 represents a balanced performance between precision and recall for the Sleep class. The support value of 81,818 signifies the number of instances in the Sleep class.

Finally, for the Work class, the precision of 0.97 indicates a high level of accuracy, with 97% of instances predicted as Work being correct. The recall value of 0.92 suggests that 92% of the actual Work instances were correctly identified by the model. The F1-score of 0.94 represents a good balance between precision and recall for the Work class. The support value of 20,763 indicates the number of instances in the Work class. Figure 11 illustrate the results.

	precision	recall	f1-score	support
anomaly	0.58	0.82	0.68	790
eat	0.98	0.95	0.96	196344
leisure	0.98	0.97	0.97	179101
other	0.89	0.99	0.94	97503
personal	0.97	0.95	0.96	246838
sleep	0.93	0.94	0.94	81818
work	0.97	0.92	0.94	20763

Fig. 11. Decision Tree classification report.

C. Random Forest Results

The provided confusion matrix in Figure 12 represents the classification results of a RF model for a multi-class classification problem. Starting with the Personal class, the confusion matrix indicates that 647 instances were correctly classified as Personal. However, there was 1 instance mistakenly classified as Personal when it belonged to another class. Additionally, 138 instances were incorrectly classified as other classes when they actually belonged to the Personal class. On the positive side, 4 instances were correctly classified as other classes. Moving on to the Heat class, the confusion matrix shows that 185,800 instances were correctly classified as Heat. However, there were 261 instances incorrectly classified as Heat when they belonged to other classes. Furthermore, 3,619 instances were mistakenly classified as other classes when they actually belonged to the Heat class. On the positive side, 6,664 instances were correctly classified as other classes.

Regarding the Leisure class, the confusion matrix indicates that 173,619 instances were correctly classified as Leisure. There were 3,099 instances incorrectly classified as Leisure when they belonged to other classes. Moreover, 974 instances were mistakenly classified as other classes when they actually belonged to the Leisure class. On the positive side, 729 instances were correctly classified as other classes .

For the Other class, the confusion matrix reveals that 96,521 instances were correctly classified as Other. There were 970 instances incorrectly classified as Other when they belonged to other classes. Surprisingly, only 12 instances were mistakenly classified as other classes when they belonged to the Other class. However, there were no instances correctly classified as other classes.

Examining the Sleep class (label 4), the confusion matrix shows that 234,111 instances were correctly classified as Sleep. There were 4,215 instances incorrectly classified as Sleep when they belonged to other classes. Additionally, 6,457 instances were mistakenly classified as other classes when they actually belonged to the Sleep class. On the positive side, 4284 instances were correctly classified as other classes. In the case of the Work class, the confusion matrix indicates that 77,318 instances were correctly classified as Work. There were 118 instances incorrectly classified as Work when they belonged to other classes. Moreover, 62 instances were mistakenly classified as other classes when they actually belonged to the Work class. On the positive side, 66 instances were correctly classified as other classes. Finally, for the Anomaly class, the confusion matrix shows that 19,045 instances were correctly classified as Anomaly. There were 38 instances incorrectly classified as Anomaly when they belonged to other classes. Furthermore, 552 instances were mistakenly classified as other classes when they actually belonged to the Anomaly class. On the positive side, 240 instances were correctly classified as other classes.

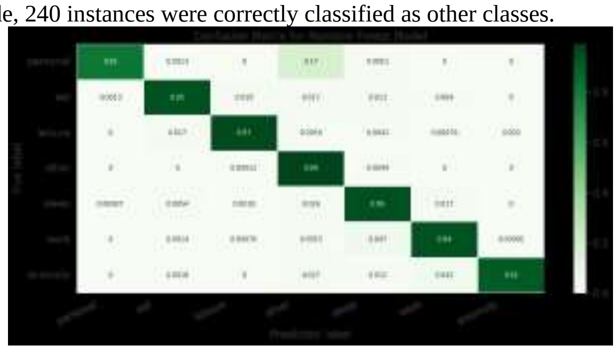

Fig. 12. Random Forest confusion matrix.

The classification report results are illustrated in Figure 13. Starting with the Anomaly class, the precision is calculated to be 0.58, indicating that 58% of instances predicted as Anomaly were correct.

The recall value of 0.82 implies that 82% of actual Anomaly instances were correctly identified by the model. The F1-score, which combines precision and recall, is 0.68. The support value for the Anomaly class is 790, representing the number of instances belonging to this class. Moving on to the Eat class, the precision is measured at 0.98, indicating a high level of accuracy in predicting Eat. The recall value of 0.95 implies that 95% of actual Eat instances were correctly classified by the model. The F1-score for Eat is 0.96, representing a good overall performance. The support value for Eat is 196,344.

For the Leisure class, the precision is determined to be 0.98, reflecting a high accuracy in predicting Leisure. The recall value is 0.97, indicating that 97% of actual Leisure instances were correctly identified by the model. The F1score for Leisure is 0.97, suggesting a balanced performance between precision and recall. The support value for Leisure is 179,101. Regarding the Other class, the precision is 0.89, implying an 89% accuracy in predicting Other. The recall value of 0.99 indicates that 99% of actual Other instances were correctly classified by the model. The F1-score for Other is 0.94, indicating a relatively good balance between precision and recall. The support value for Other is 97,503. Examining the Personal class, the precision is calculated to be 0.97, indicating a 97% accuracy in predicting Personal. The recall value of 0.95 implies that 95% of actual Personal instances were correctly identified by the model. The F1-score for Personal is 0.96, representing a good overall performance. The support value for Personal is 246,838. Moving to the Sleep class, the precision is determined to be 0.93, implying a 93% accuracy in predicting Sleep. The recall value of 0.94 indicates that 94% of actual Sleep instances were correctly classified by the model. The F1-score for Sleep is 0.94, suggesting a balanced performance between precision and recall. The support value for Sleep is 81,818. Finally, for the Work class, the precision is measured at 0.97, indicating a high level of accuracy of 97% in predicting Work. The recall value of 0.92 implies that 92% of actual Work instances were correctly classified by the model. The F1-score for Work is 0.94, representing a good balance between precision and recall. The support value for Work is 20,763. Considering all the classes, the overall accuracy of the RF model is calculated to be 95.61%.

	precision	recall	f1-score	support
anomaly	0.58	0.82	0.68	790
eat	0.98	0.95	0.96	196344
leisure	0.98	0.97	0.97	179101
other	0.89	0.99	0.94	97503
personal	0.97	0.95	0.96	246838
sleep	0.93	0.94	0.94	81818
work	0.97	0.92	0.94	20763

Fig. 13. Random Forest classification report.

D. Logistic Regression Results

The confusion matrix in Figure Figure 14 represents the classification results for a multi-class problem using an unspecified model. The matrix consists of rows and columns, with each row representing the actual labels and each column representing the predicted labels. Starting with the first row, it shows the instances that were predicted as Personal. Out of the instances that truly belong to the Personal class, 168 were correctly classified as Personal. However, there were 122 instances that were wrongly predicted as Eat, 49 as Leisure, 18 as Other, 433 as Sleep, and none as Work or Anomaly.

Moving on to the second row, it represents the instances predicted as Eat. Out of the instances that truly belong to the Eat class, only 5 were correctly classified as Eat. However, there were 179,998 instances that were mistakenly predicted as Personal, 5,601 as Leisure, 3,812 as Other, 5,588 as Sleep, 1,147 as Work, and 193 as Anomaly.

The third row represents the instances predicted as Leisure. Among the instances that truly belong to the Leisure class,

169,648 were correctly classified as Leisure. However, there were 6,541 instances that were wrongly predicted as Personal, 1,233 as Eat, 597 as Other, 197 as Sleep, 843 as Work, and none as Anomaly.

The fourth row represents the instances predicted as Other. Out of the instances that truly belong to the Other class, 92,918 were correctly classified as Other. However, there were 661 instances that were mistakenly predicted as Personal, 108 as Eat, 3,608 as Leisure, 189 as Sleep, and none as Work or Anomaly. The fifth row represents the instances predicted as Sleep. Among the instances that truly belong to the Sleep class, 228,444 were correctly classified as Sleep. However, there were 2,791 instances that were wrongly predicted as Personal, 1,520 as Eat, 5,909 as Leisure, 8,100 as Other, 53 as Work, and none as Anomaly.

Moving on to the sixth row, it represents the instances predicted as Work. Out of the instances that truly belong to the Work class, 67,725 were correctly classified as Work. However, there were 516 instances that were mistakenly predicted as Personal, 62 as Eat, 638 as Leisure, 12,811 as Other, 66 as Sleep, and none as Anomaly. The final row represents the instances predicted as Anomaly. Among the instances that truly belong to the Anomaly class, 19,052 were correctly classified as Anomaly (true positives). However, there were none predicted as Personal, Eat, Leisure, Other, Sleep, or Work.

By examining this detailed confusion matrix, we can gain insights into the model's performance for each class, including the number of true positives and the instances misclassified as other classes. This information helps us assess the strengths and weaknesses of the model in accurately predicting the different classes.

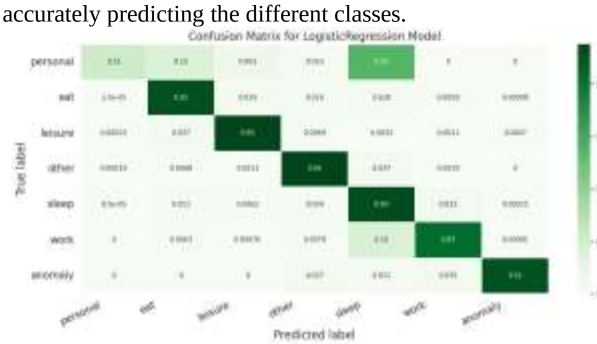

Fig. 14. Logistic Regression confusion matrix.

Starting with the Anomaly class, the precision of 0.66 suggests that 66% of instances predicted as Anomaly were correctly classified. The recall value of 0.21 indicates that only 21% of actual Anomaly instances were identified by the model. The F1-score, which considers both precision and recall, is 0.32, representing a balance between the two metrics. The support value for the Anomaly class is 790, indicating the number of instances belonging to this class.

Moving to the Eat class, the precision of 0.94 indicates a high level of accuracy in predicting Eat. The recall of

0.92 suggests that 92% of actual Eat instances were correctly classified by the model. The F1-score of 0.93 represents a good overall performance in terms of precision and recall for the Eat class. The support value for Eat is 196,344.

For the Leisure class, the precision is 0.96, indicating a high accuracy in predicting Leisure. The recall value of 0.95 implies that 95% of the actual Leisure instances were correctly identified by the model. The F1-score of 0.95 suggests a balanced performance between precision and recall for the Leisure class. The support value for Leisure is 179,101. Regarding the Other class, the precision of 0.88 represents an 88% accuracy in predicting Other. The recall of 0.95 suggests that 95% of the actual Other instances were correctly classified by the model. The F1-score of 0.92 indicates a relatively good balance between precision and recall for the Other class. The support value for Other is 97,503.

Moving to the Personal class, the precision of 0.91 suggests a 91% accuracy in predicting Personal. The recall of 0.93 implies that 93% of the actual Personal instances were correctly identified by the model. The F1-score of 0.92 represents a good overall performance in terms of precision and recall for the Personal class. The support value for Personal is 246,838.

Looking at the Sleep class, the precision of 0.87 indicates an 87% accuracy in predicting Sleep. The recall of 0.83 suggests that 83% of the actual Sleep instances were correctly classified by the model. The F1-score of 0.85 represents a balance between precision and recall for the Sleep class. The support value for Sleep is 81,818.

Finally, for the Work class, the precision of 0.94 indicates a high level of accuracy, with 94% of instances predicted as Work being correct. The recall of 0.92 suggests that 92% of the actual Work instances were correctly identified by the model. The F1-score of 0.93 represents a good balance between precision and recall for the Work class. The support value for Work is 20,763. The accuracy of the model is reported as 92.07%, reflecting the percentage of correctly classified instances across all classes. The classification report results are illustrated in Figure 15.

	precision	recall	f1-score	support
anomaly	0.66	0.21	0.32	790
eat	0.94	0.92	0.93	196344
leisure	0.96	0.95	0.95	179101
other	0.88	0.95	0.92	97503
personal	0.91	0.93	0.92	246838
sleep	0.87	0.83	0.85	81818
work	0.94	0.92	0.93	20763

Fig. 15. Logistic Regression classification report.

E. Multinomial Naive Bayes

Looking at the matrix in Figure 16, we can see that in the first row, none of the instances that truly belong to the Personal class were correctly classified as Personal. However, there were 243 instances that were mistakenly predicted as Eat, 65 as Leisure, and 482 as Sleep. Moving on to the second row, it represents instances predicted as Eat. Out of the instances that truly belong to the Eat class, 165,127 were correctly classified as Eat (true positives). However, there were 22,635 instances that were wrongly predicted as Personal, 1,928 as Leisure, 6,636 as Other, 3 as Sleep, and 15 as Work. The third row represents the instances predicted as Leisure. Among the instances that truly belong to the Leisure class, 175,531 were correctly classified as Leisure (true positives). However, there were 1,992 instances that were wrongly predicted as Personal, 261 as Eat, 1,176 as Other, and 141 as Sleep.

The fourth row represents the instances predicted as Other. Out of the instances that truly belong to the Other class, 63,609 were correctly classified as Other (true positives). However, there were 1,607 instances that were mistakenly predicted as Personal, 1,297 as Eat, 30,313 as Sleep, and 677 as Work. The fifth row represents the instances predicted as Sleep. Among the instances that truly belong to the Sleep class, 202,329 were correctly classified as Sleep (true positives). However, there were 9,597 instances that were wrongly predicted as Eat, 4,389 as Leisure, 1,130 as Other, 29,374 as Work, and none as Anomaly.

Moving to the sixth row, it represents the instances predicted as Work. Out of the instances that truly belong to the Work class, 66,392 were correctly classified as Work (true positives). However, there were 4,129 instances that were mistakenly predicted as Personal, 770 as Eat, 44 as Leisure, 10,483 as Other, and none as Anomaly. The final row represents the instances predicted as Anomaly. Among the instances that truly belong to the Anomaly class, 17,244 were correctly classified as Anomaly (true positives). However, there were 717 instances that were wrongly predicted as Personal, 1,808 as Eat, and 994 as Other.

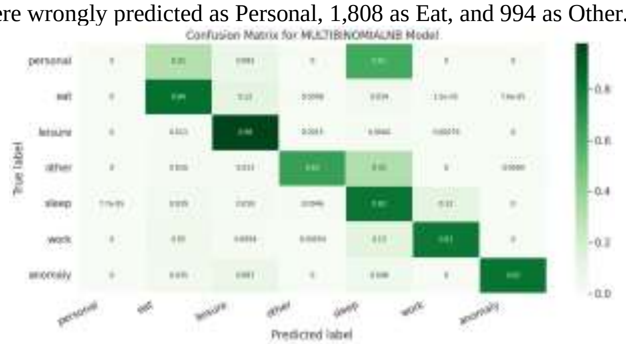

Fig. 16. Multinomial NB confusion matrix.

The model has been trained to predict one of several classes, including "anomaly", "eat", "leisure", "other", "personal", "sleep", and "work". The Random Forest classifier obtained 99% accuracy. Figure 17 shows the precision, recall, F1-score, and support. For example, for the anomaly class, the model has a precision of 0.66, a recall of 0.21, and an F1-score of 0.32.

	precision	recall	f1-score	support
anomaly	0.00	0.00	0.00	790
eat	0.90	0.84	0.87	196344
leisure	0.85	0.98	0.91	179101
other	0.95	0.65	0.77	97503
personal	0.80	0.82	0.81	246838
sleep	0.69	0.81	0.75	81818
work	0.96	0.83	0.89	20763

Fig. 17. Multinomial NB classification report.

F. Comparing the Results and Discussion

Table II provides the results that compare the performance of five different models in a classification task, based on their accuracy values. The ANN, RF, and DT models achieved similar high accuracies of 95.52%, 95.61%, and 95.61%, respectively. These models demonstrate strong classification abilities. The Multinomial NB model achieved a lower accuracy of 83.85%, suggesting slightly less accurate predictions. The LR model achieved an accuracy of 92.07%, demonstrating moderate performance.

Among the five models compared, the best performing model based on the reported accuracy values is the RF model. It achieved the highest accuracy of 95.61%, outperforming the other models including the ANN, DT, Multinomial NB, and LR models. The RF model demonstrates superior classification abilities and appears to be the most suitable choice for the given task, providing the highest level of accuracy in predicting the classes.

TABLE II MODELS RESULTS IN COMPARISON.

Method	DT	RF	ANN	LR	Mul-NB
Accuracy	95%	95%	95%	92%	83%
Precision	97%	97%	60%	94%	96%
Recall	92%	92%	81%	92%	83%
F1-score	94%	94%	69%	93%	89%

8. CONCLUSION

The aim of this research was to evaluate and compare different models for accurately recognizing and monitoring the Activities of Daily Living (ADLs) among older adults, with a specific focus on those with dementia. By assessing models such as the ANN, RF, DT, LR, and Multinomial NB, the research aimed to identify the most effective model for accurately classifying ADLs. The results of the evaluation revealed that the RF and DT model achieved the highest accuracy among the models tested with an accuracy of 95.61%. This indicates that the RF model was most successful in capturing the complex relationships and patterns present in the ADL data, leading to more precise predictions of ADL activities. The research highlights the potential of the RF model as a robust and reliable approach for ADL recognition and monitoring in older adults, particularly those with dementia.

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9. DIRECTIONS FOR FUTURE WORKS

In addition to the findings of this research, there are several avenues for future work that can enhance the understanding and application of ADL monitoring among older adults.

- Ensemble Voting: One potential avenue for future work is the exploration of ensemble voting techniques. Ensemble methods combine the predictions of multiple models to improve overall performance and robustness. In the context of ADL recognition and monitoring, ensemble voting can be applied by combining the predictions of different models, such as the RF, DT, and ANN models. By leveraging the strengths of multiple models, ensemble voting can potentially enhance accuracy, reduce bias, and improve the reliability of ADL predictions. Further research can investigate different ensemble methods, such as majority voting, weighted voting, or stacking, to determine the most effective approach for ADL monitoring.
- Explainable AI: Another important direction for future work is the integration of explainable AI techniques. Explainable AI aims to provide interpretable and transparent models that can explain the reasoning behind their predictions. This is particularly relevant in the context of ADL monitoring, as it is crucial for caregivers and healthcare professionals to understand the factors that contribute to

the prediction of specific ADLs. By employing explainable AI techniques, such as feature importance analysis, rule extraction, or model-agnostic explanations, the models' decision-making processes can be made more transparent and understandable. This can help build trust, enhance the acceptance of ADL monitoring systems, and facilitate effective decision-making by caregivers and healthcare providers.

- Real-world Deployment and Validation: Future research should also focus on the real-world deployment and validation of ADL monitoring systems. Conducting studies in real-world settings, such as assisted living facilities or home environments, can provide valuable insights into the practical challenges and opportunities of implementing ADL monitoring technologies. This includes considerations related to sensor placement, data collection procedures, privacy concerns, and user acceptance. Realworld validation studies can assess the accuracy, usability, and effectiveness of ADL monitoring systems, providing evidence for their practical benefits and informing potential improvements.

Longitudinal Studies and Predictive Modelling: Longitudinal studies that extend over an extended period can offer deeper insights into the progressive changes in ADL behaviour among older adults. By collecting data at multiple time points, researchers can identify patterns, trends, and early indicators of functional decline or changes in ADL performance. This can be facilitated through the development of predictive modelling techniques that leverage longitudinal data to forecast future ADL behaviour. Long-term monitoring and prediction of ADLs can support proactive interventions, personalized care plans, and early detection of deviations from normal behaviour.

10. REFERENCES

[1] S. Alghamdi, E. Fadel, and N. Alowidi. Recognizing activities of daily living in ambient intelligence environments using 1d convolutional neural networks. *IJARCCE*, 9:1–8, 03 2020.

[2] T. Alshammari, N. Alshammari, M. Sedky, and C. Howard. Simadl: simulated activities of daily living dataset. *Data*, 3(2):11, 2018.

[3] D. Arifoglu and A. Bouchachia. Activity recognition and abnormal behaviour detection with recurrent neural networks. *Procedia Computer Science*, 110:86–93, 2017.

[4] D. Arifoglu, Y. Wang, and A. Bouchachia. Detection of dementia-related abnormal behaviour using recursive auto-encoders. *Sensors*, 21(1):260, 2021.

[5] J. C. Augusto. Ambient intelligence: Basic concepts and applications. In *Software and Data Technologies: First International Conference, ICSOFT 2006, Setubal, Portugal, September 11-14, 2006, Revised´ Selected Papers 1*, pages 16–26. Springer, 2008.

[6] R. Casas, R. B. Mar´ın, A. Robinet, A. R. Delgado, A. R. Yarza, J. Mcginn, R. Picking, and V. Grout. User modelling in ambient intelligence for elderly and disabled people. In *International Conference on Computers for Handicapped Persons*, pages 114–122. Springer, 2008. [7] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002.

[8] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu. Elderly activities recognition and classification for applications in assisted living. *Expert Systems with Applications*, 40(5):1662–1674, 2013.

[9] K. Ducatel, U. europeenne. Technologies de la soci´ et´ e de l'information,´
U. europeenne. Institut d'´ etudes de prospectives technologiques, and´ U. europeenne. Soci´ et´ e de l'information conviviale.´ Scenarios for ambient intelligence in 2010. 2001.

[10] A. Elbayoudi, A. Lotfi, and C. Langensiepen. The human behaviour indicator: A measure of behavioural evolution. *Expert Systems with Applications*, 118:493–505, 2019.

[11] R. Gomez Ramos, J. Duque Domingo, E. Zalama Casanova, J. G´ omez´ Garc´ıa-Bermejo, et al. Daily human activity recognition using nonintrusive sensors. 2021.

[12] W. James. *Psychology, briefer course*, volume 14. Harvard University Press, 1984.

[13] O. D. Lara and M. A. Labrador. A survey on human activity recognition using wearable sensors. *IEEE Communications Surveys and Tutorials*, 15(3):1192–1209, 2013.

[14] A. Lotfi, C. Langensiepen, S. M. Mahmoud, and M. J. Akhlaghinia. Smart homes for the elderly dementia sufferers: identification and prediction of abnormal behaviour. *Journal of ambient intelligence and humanized computing*, 3:205–218, 2012.

[15] A. Newell, H. A. Simon, et al. *Human problem solving*, volume 104. Prentice-hall Englewood Cliffs, NJ, 1972.

[16] Q. Ni, A. B. Garc´ıa Hernando, and I. P. de la Cruz. The elderly's independent living in smart homes: A characterization of activities and sensing infrastructure survey to facilitate services development. *Sensors*, 15(5):11312–11362, 2015.

[17] V. G. Sanchez, O. M. Lysaker, and N.-O. Skeie.´ Human behaviour modelling for welfare technology using hidden markov models. *Pattern Recognition Letters*, 137:71–79, 2020.

[18] T.-H. Tan, L. Badarch, W.-X. Zeng, M. Gochoo, F. S. Alnajjar, and J.W. Hsieh. Binary sensors-based privacy-preserved activity recognition of elderly living alone using an rnn. *Sensors*, 21(16):5371, 2021.

[19] A. Wang, S. Zhao, C. Zheng, J. Yang, G. Chen, and C.-Y. Chang. Activities of daily living recognition with binary environment sensors using deep learning: A comparative study. *IEEE Sensors Journal*, 21(4):5423–5433, 2020.

[20] S. Wild, G. Roglic, A. Green, R. Sicree, and H. King. Global prevalence of diabetes: estimates for the year 2000 and projections for 2030.
Diabetes care, 27(5):1047–1053, 2004.