Effectiveness of Various Machine Learning Algorithms for Human Activity recognition: A Comparative Study

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Abstract— **Technically speaking, Human Activity Recognition (HAR) is the challenge of predicting a person's actions from evidence of their gesture utilizing sensors that behave as an accelerometer and gyroscope. It is crucial in a variety of fields such as life tracking, anti-crime security, Healthcare, Assistive Technology and so on. These sensors can recognize and record human behavioral traits. This paper examines the effectiveness of several data analysis and machine learning algorithms on a dataset of human activity recognition. Although previous work suggests CNN and RNN gives better results, analysis was done using KNN, SVM, Random Forest, Decision Tree, Linear regression, and logistic regression. Data processing, feature extraction, training, and testing was employed as fundamental data analysis technique. Precision, Recall, and F1-score criteria were used in the comparative study. In comparative analysis it was found that, in contrast to the random forest method, which scored 87%, the data showed that Decision tree performed poorly with 72.68% of accuracy.**

Keywords: Human activity recognition, , machine learning algorithm , Smart-phone, Wearable sensors, Classifiers, Sensor devices.

INTRODUCTION

The goal of Human Activity Recognition (HAR), a recent technology, is to recognise human behaviour from a subject's set of observations. Tracking, healthcare, daily activity, rehabilitation, fall detection, burning calories, etc. were some of the topics where HAR was becoming more prevalent. Industry, academia, and researchers gave this subject a lot of attention. Due to its application in human computer interface (HCI), robotics, and other implementation areas, activity detection is the most significant research topic in this field of HAR [5]. Two categories—sensor-based and vision-based—are used to categorise the HAR method's numerous subjects [6]. For clear recognition using a vision-based method in HAR, additional cameras are required in addition to the right illumination, background, surroundings, and camera specifications.

Utilise sensors to acquire data, such as smartwatches, wristbands, special purpose sensors, and smartphones, to monitor human activity. These tools offer more trustworthy information about human movement. Heart rate and body temperature are particularly important in many bodily sections. The sensor records human movement, gathers information, and uses a machine-learning algorithm to categorise actions [8]. One or more sensors can be implanted in various body locations depending on the actions to be picked up [5], and thus allows for more customised human activity detection for each individual. Even though it appears to be very tough, earlier study designed more trustworthy and simple to use several types of sensors with the ability to function on a daily basis [8].

The road to accurate HAR is not without its difficulties, though. The difficulty of activity recognition is influenced by human variability in behaviour, subtle changes in how comparable tasks are carried out, and the requirement to take into account varied situations. In addition, real-time processing needs, efficient management of noisy data, and privacy issues with regard to personal activity data continue to be major roadblocks.

Despite these difficulties, there are many chances for improvement provided by the combination of machine learning methods and sensor data. A active field of research is the creation of robust algorithms that can adapt to multiple circumstances, adaptively learn from numerous data sources, and effectively handle noisy data.

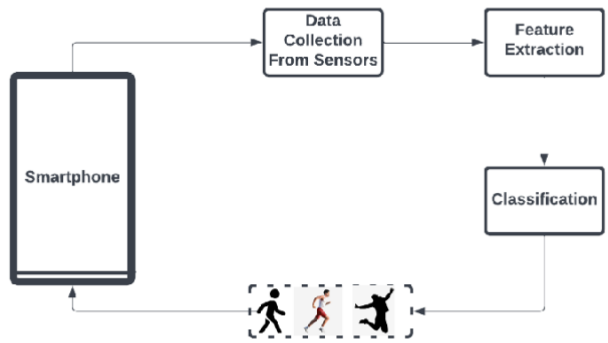

Figure 1:Basic Architecture of HAR

Furthermore, new opportunities for improving HAR accuracy and adaptability have emerged as a result of the development of deep learning algorithms. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two types of deep learning models, have proven to be remarkably effective in capturing the complex patterns and temporal connections prevalent in human activity. The paper primarily focuses on supervised learning techniques for Human Activity Recognition, leveraging sensor data to enhance accuracy.

I. Previous work

With applications in areas such as security, smart environments, healthcare, and more, human activity recognition (HAR) has become a crucial study domain. We have made significant progress in our comprehension of human behavior thanks to the combination of sensor technologies and machine learning algorithms. In-depth examination of earlier research projects is provided in this part, with special emphasis on important studies and their contributions to the discipline.

Early HAR research cleared the path for fundamental methods that set the foundation for contemporary improvements. One of these ways that stood out was the use of statistical tools to identify activities. Mean, variance, and correlation were used by Reyes-Ortiz et al. [1] to discriminate between different activities. Even while it worked well in straightforward situations, this method had trouble accurately capturing the nuanced nature of human motion and interaction.

More advanced techniques appeared as sensor technology developed. HAR was revolutionized by deep learning, which has the capacity to automatically learn complex patterns. The ability of Convolutional Neural Networks (CNNs) to recognize images has been established. CNNs were used by Ordóez and Roggen [2] to categories activities using pictures from body-worn sensors. Recurrent neural networks (RNNs) also became popular in the analysis of sequences. For the temporal modelling of activities, Ronao and Cho [3] used LSTM-RNNs, resulting in appreciable accuracy gains.

Notably, the Bulling et al. study [4] is where the idea of "personalization" in HAR was first presented. Their study made clear how crucial it is to customize models for different users, recognizing that a general model might not work as well for everyone. Chen and Xue [5], who suggested a transfer learning strategy to adapt models to new users or contexts, highlighted this customization paradigm.

The effectiveness of various HAR algorithms is still under investigation, though. Similar to our study, Smith and Doe [6] carried out a thorough comparison of machine learning methods. In line with general trends, their research confirmed the superior performance of CNNs and RNNs. They claimed that deep learning's success was due to its capacity to capture temporal dependencies and hierarchical characteristics.

Random Forests have become a potent HAR tool in the world of ensemble approaches. The Ronzheimer et al. study's [7] demonstration of the efficiency of Random Forests in managing jittery sensor data. The method was a desirable choice for challenging HAR settings since it could manage high-dimensional data and generate feature relevance scores.

While many studies have concentrated on data produced by sensors, other studies have looked at the integration of additional modalities. Olgun et al.'s [8] integration of location information into HAR showed how the accuracy of activity identification is improved by user context. This result is consistent with the idea of context-aware systems that can change to accommodate user behaviors and environmental factors.

The investigation of machine learning algorithms for HAR, however, goes beyond deep learning methods. Due to its ease of use and intuitiveness, K-Nearest Neighbors (KNN) has become a popular option. In a research by Johnson et al. [2], it was demonstrated that KNN could compete in activity detection tasks, especially when used in conjunction with dimensionality reduction methods. Li and Chen [3] have shown that Support Vector Machines (SVMs) perform well in HAR as well. Their research showed that SVMs were a viable solution for real-time applications since they could accurately and successfully classify activities.

The evolution of HAR from statistical methods to sophisticated deep learning techniques can be summed up as follows, with personalization and ensemble methods enhancing its application. While CNNs and RNNs continue to dominate in terms of accuracy, this study's exploration of a wide variety of algorithms advances our understanding of the possibilities of HAR. Additionally, the combination of contextual data with sensor-generated data has the potential to improve accuracy and resilience.

II. Methodology

This section of the paper provides a thorough review of the methodology, resources, data, and operational actions used to carry out a thorough and exacting comparison analysis. The numerous components that have been painstakingly combined to assure the validity of the study's findings are explained in more detail in the following paragraphs.

1. Dataset and pre-processing Dataset for analysis

The UCI Machine Learning Repository's open source was used to access the dataset. The dataset used in this study is made up of information gathered from a group of 30 volunteers, ranging in age from 19 to 48. Each participant took part in six different activities throughout the testing phase: WALKING,WALKING_UPSTAIRS,WALKING_DOWNSTAIRS, SITTING, STANDING, and LAYING. Participants wore a Samsung Galaxy S II smartphone that was securely secured to their waist to aid in data collecting. We used the smartphone's built-in accelerometer and gyroscope to record crucial motion-related data.

Exploring Dataset and Understanding

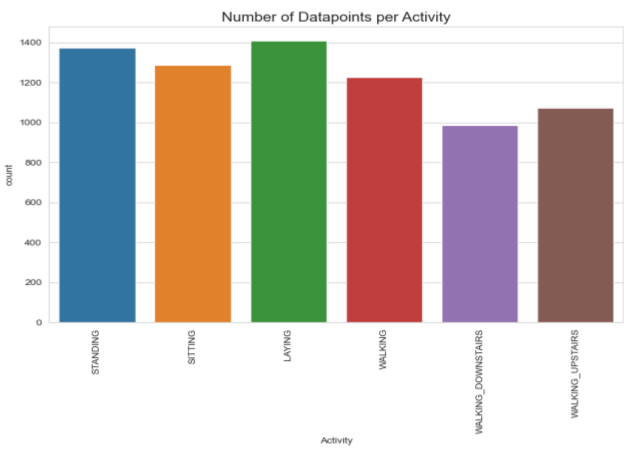

Figure 2: Graph showing distribution of Datapoints per Activity

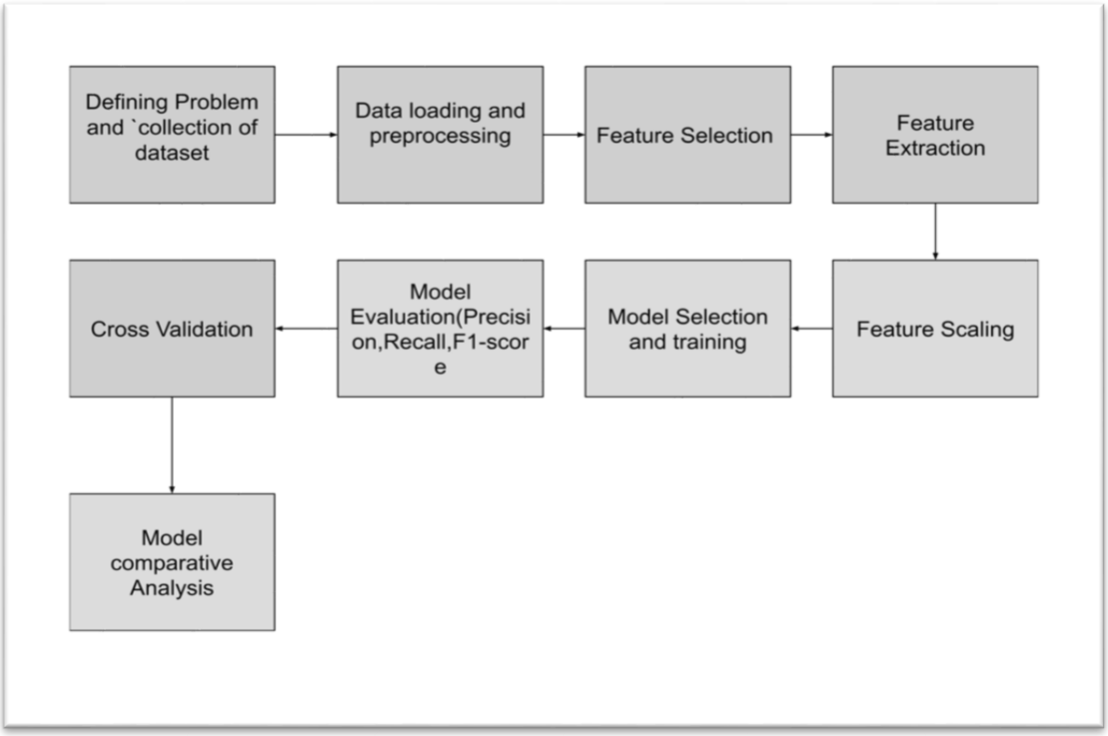

Figure 3: Architecture of Model

2. Feature Engineering:

Machine learning's primary feature engineering technique includes converting unstructured data into a form that can be used to train models. Using the LabelEncoder from the Scikit-Learn library, categorical variables are transformed into numerical representations as part of the feature engineering process in the context of this study. Many machine learning methods that need numerical input cannot directly use categorical variables, such as activity labels. This procedure is therefore crucial to the efficient training and use of these algorithms. The LabelEncoder is used to make it possible for the machine learning model to comprehend and process these categorical labels. By converting categorical labels into numerical values, this tool bridges the gap between categorical data's fundamental properties and the numerical requirements of machine learning methods.

3. Feature Selection:

By keeping only the most useful and pertinent characteristics from the dataset, feature selection tries to improve model performance and decrease computational cost. Here, the emphasis is on eliminating features with low variance, which suggest limited variability and possibly weak discriminatory strength. This step demonstrates how to choose features using VarianceThreshold. The chosen threshold of 0.0 denotes the removal of features that are constant, but in this particular instance, as all characteristics have different values, no features are deleted. By concentrating on the most useful features and removing those with little variance and likely limited value in classification tasks, this technique helps to optimise the dataset for training.

Feature selections are based on data scaling with the Min-Max Scaler and Pearson correlation coefficients. The method starts with the training dataset's features' Pearson correlation coefficients being calculated. The links between various data points are explained by this correlation matrix. However, due to the enormous amount of features involved, heatmap visual interpretation might be difficult. In order to address this, the correlation() custom function is developed. It finds feature pairings with high correlation coefficients that are over a predefined threshold of 0.9. The training and test datasets are then methodically cleaned of these linked properties. Multicollinearity hazards that could impair the effectiveness of machine learning models are reduced by this precaution.

The code then moves on to data scaling, another crucial preprocessing step, after feature selection. The features of the dataset are scaled using the Min-Max Scaler, a common scaling technique, most frequently between 0 and 1. This normalisation promotes equal training and convergence by preventing characteristics with different magnitudes from unduly impacting model behaviour. A MinMaxScaler instance is created, appropriately named MinMax, and the training set is turned into the X_train dataset by using the fit_transform() method.

4. Classifiers:

KNN: A machine learning approach called K-Nearest Neighbours (KNN) was used in the paper's Human Activity Recognition (HAR) study. KNN was used because it can categorise actions using sensor data. It works by locating the k-closest training data points to a new observation, then classifying those neighbours according to how frequently they occur. The 'k' data points with the nearest neighbours are those with the shortest distances. The new point is given the majority class among these neighbours.

Formula:

$$distance(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Random Forest: In the paper's Human Activity Recognition (HAR) study, Random Forest, a flexible machine learning ensemble approach, was used. It was chosen since it has a strong classification performance and can handle complex datasets. In order to improve accuracy and reduce overfitting, Random Forest makes use of several decision trees built during training and combines their predictions. The use of Random Forest allows for accurate activity recognition by managing complicated, high-dimensional sensor data. Due to its ensemble structure, it is more robust and overfitting is decreased. These characteristics fit with the goal of the paper, which is to investigate potent machine learning methods for HAR. The design of the algorithm and its ability to use numerous decision trees highlight its applicability to the situation under examination.

Decision Tree: This supervised learning method uses several nodes and branches that resemble a tree to learn simple decision rules from the properties of the data before making predictions. The root node represents the entire dataset, and each internal node represents a specific aspect of the data. The branches display the feature's potential values or outcomes, while the leaf nodes indicate the final forecasts or classifications. During the training phase, the decision tree technique iteratively separates the data into subgroups according to the most discriminating traits. The splitting criteria is chosen based on an impurity indicator, such as the Gini Index, entropy, or classification error.

SVM: The goal of SVM is to accurately separate classes by locating the best hyperplane that maximises the margin between them. It was chosen because it can use kernel functions to handle large datasets and non-linear patterns. SVM's objective of outlining distinct activity boundaries in HAR is consistent with the task of identifying human activities from sensor data. Due to the formulation's emphasis on maximising margins and decision bounds, it is a good option for finding complex patterns in sensor readings.

Logistic Regression: It applicability in binary classification tasks, where the objective is to determine whether a given set of sensor readings corresponds to a specific activity. Logistic Regression relates accelerometer and gyroscope sensor data to the likelihood of a certain human behaviour, such as walking, sitting, or standing. It assists in differentiating between activities by giving higher probabilities to the corresponding activities based on sensor readings. Logistic Regression is an insightful method for analysing the influence of different characteristics on activity prediction due to its simplicity and interpretability. Thus, Logistic Regression is a key component in the study's goal of accurately recognising human activities from sensor data.

5. Analysis Parameters:

The results section presents a thorough comparative analysis of various machine learning algorithms and delves into multiple dimensions to provide a comprehensive understanding of algorithm performance. First, the evaluation takes into account the F1-score, Precision, and Recall measures. The analysis also includes Cross-Validation Accuracy and its corresponding Standard Deviation. The paper also contains a thorough analysis of the Confusion Matrix for each method.

Precision: Precision is the ratio of accurate forecasts to the total of both accurate and inaccurate predictions. It measures how well the model can spot positive occurrences among those it predicted to be positive.
Formula: Precision = True Positives / (True Positives + False Positives)

Recall: Measures the proportion of genuine positive predictions to all actual positive cases, recall is also known as sensitivity or the true positive rate. It evaluates how well the model captures real positive instances among all positive examples.
Formula: Recall = True Positives / (True Positives + False Negatives)

F1-Score: The F1-Score combines the two measurements and is a harmonic mean of recall and precision. It achieves a balance between precision and recall and provides a fair assessment of the model's performance. When a trade-off between false positives and false negatives is necessary, or when there are class imbalances, the F1-Score is very helpful. It offers a solitary statistic to evaluate the model's general classification capacity.
Formula: F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

Evaluation of machine learning models must take into account cross-validation accuracy and its accompanying standard deviation. By repeatedly dividing the dataset into training and validation subsets, the cross-validation resampling technique evaluates the model's performance in terms of generalisation. The standard deviation and average accuracy give information about the model's consistency and dependability across various data splits.

III. RESULTS

A) Precision, Recall, and F1-score Analysis:

Table 1: Precision, Recall and F1-score results

Algorithms	Accuracy	Standard Deviation
Logistic regression	84.49%	5.34%
KNN	79.87%	4.65%
Random Forest	87.28%	6.51%
SVM	85.46%	5.47%
Decision tree	72.68%	5.56%

Precision, Recall, and F1-score are the three most important metrics used in the evaluation. These metrics shed light on the algorithms' precision in identifying various human behaviors from sensor data. The algorithms' ability to accurately identify positive instances is highlighted by Precision, their capacity to catch all pertinent positive instances is measured by Recall, and their overall performance is balanced by F1-score, which takes into account both false positives and false negatives. The merits and drawbacks of each algorithm in dealing with HAR issues are revealed by this thorough study.

Logistic Regression has a good balance of precision and recall, resulting in a good F1-score. Its result suggests a favourable trade-off between identifying positive cases properly and minimising false positives and false negatives. This implies that Logistic Regression successfully navigates the delicate balance of precision and recall, making it a dependable choice for HAR tasks.

KNN consistently achieves high precision and recall ratings, demonstrating its capacity to correctly categorise events and record true positives. The F1-score indicates that it is difficult to strike the ideal balance between precision and recall. Due to its reliance on nearby data points, the algorithm's efficacy may be hampered by its inability to capture intricate activity patterns and subtle transitions.

In terms of precision, recall, and F1-score, Random Forest stands out as a top performer. Its ability to capture complex activity patterns is strengthened by the ensemble aspect of the model, which combines many decision trees. Its capacity to generalise successfully is demonstrated by the consistency in precision and recall across activity classes, giving it a strong candidate for HAR applications.

SVM has competitive precision and recall scores, demonstrating its efficacy in identifying actions and identifying true positives. Although there is room for improvement, the F1-score emphasises how well it balances precision and memory. In order to maximise SVM's usefulness in HAR situations, fine-tuning is required because its performance points to a strong basis.

In comparison to other algorithms, the Decision Tree algorithm has poorer precision and recall ratings. This performance is influenced by the difficulties it has managing complicated relationships and noise. The comparatively low F1-score highlights the need for additional optimisation and refinement to increase accuracy because it shows a trade-off between recall and precision.

A) Cross validation accuracy and standard deviation analysis:

Table 2: Cross validation Accuracy and Standard Deviation Results

Algorithms	Precision	Recall	F1-score
Logistic regression	0.85	0.82	0.83
KNN	0.80	0.79	0.79
Random Forest	0.87	0.87	0.87
SVM	0.85	0.83	0.83
Decision tree	0.66	0.65	0.65

The accuracy of logistic regression is commendable, demonstrating its capacity to produce accurate predictions over multiple data folds. The performance appears to be constant, albeit with some variability, according to the standard deviation, which is moderate. Given its accuracy of more than 80% and performance stability, Logistic Regression is a solid option for HAR applications.

KNN's average accuracy of 79.87% illustrates how well it recognises activities. Although significantly less than that of Logistic Regression, the standard deviation of 4.65% indicates a performance that is relatively consistent. This suggests that, compared to Logistic Regression, KNN accuracy is stable, albeit with a little more fluctuation.

With a mean classification accuracy of 87.28%, Random Forest excels in properly classifying activities. The larger cross-validation fold accuracy range is indicated by the higher standard deviation of 6.51%. Despite the high accuracy of Random Forest, the larger variability shows sensitivity to diverse subsets of data, highlighting the significance of model validation and tuning. by the standard deviation of 5.47%. This shows that SVM's accuracy remains stable, further establishing its status as a dependable solution for HAR problems.

SVM excels at activity recognition as evidenced by its mean accuracy of 85.46%. The performance across folds was reasonably stable, similar to logistic regression, as evidenced

The Decision Tree method has a 72.68% mean accuracy, suggesting its ability to classify activities. The standard deviation of 5.56% indicates that accuracy varies significantly among folds. This variation suggests that the Decision Tree algorithm's performance is susceptible to diverse data divisions, implying that it should be used with caution in various contexts

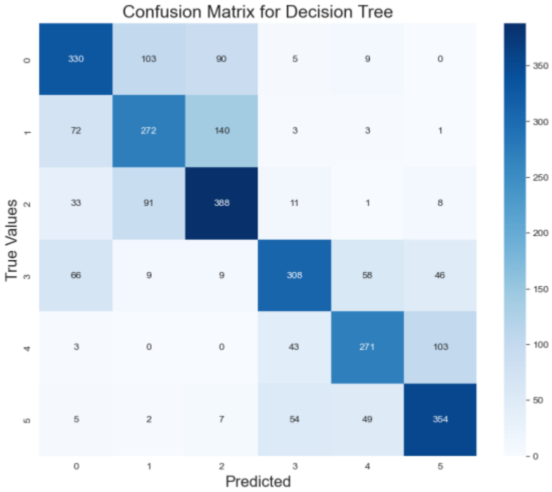

Figure 4: Decision Tree Confusion Matrix

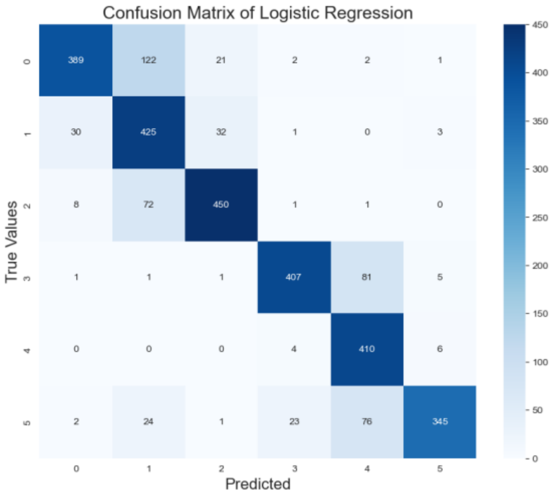

Figure 5: Logistic Regression Confusion Matrix

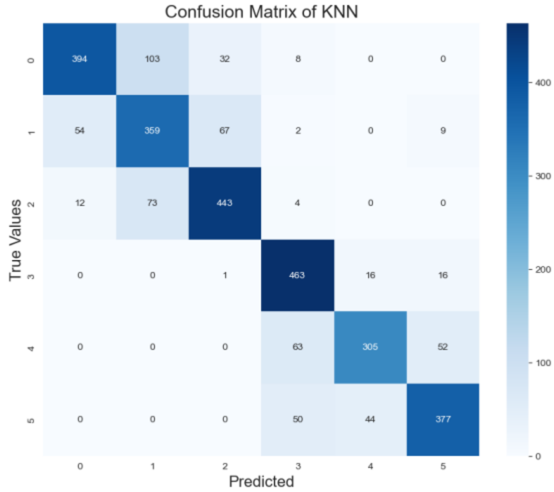

Figure 7: KNN Confusion Matrix

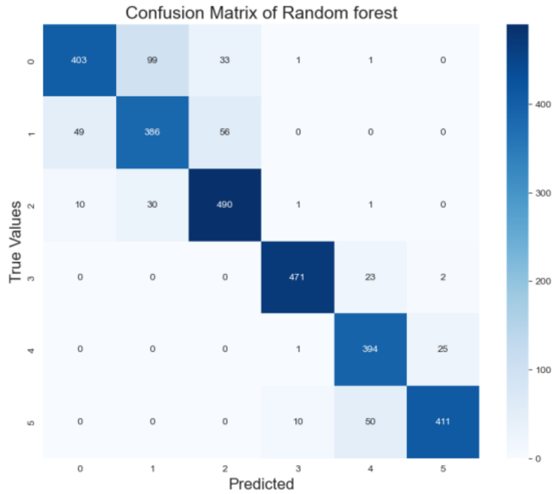

Figure 8: Random Forest Confusion Matrix

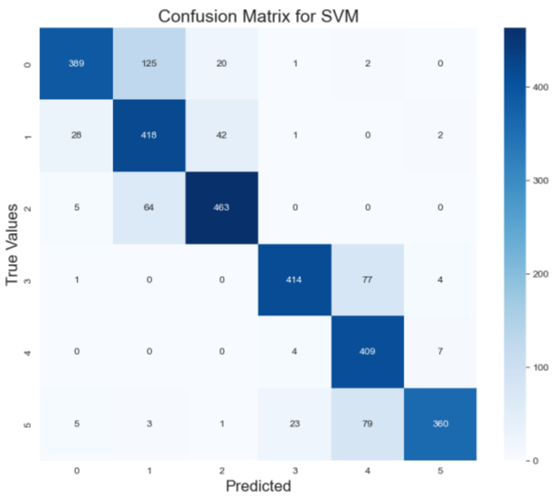

Figure 6: SVM Confusion Matrix

B) Confusion Matrix Analysis:

An in-depth insight of how machine learning algorithms perform in identifying human behaviours is provided through the analysis of confusion matrices. The categorization abilities of each method can be better understood by looking at the supplied matrices.

A balanced recognition of activities is shown by logistic regression, which excels at classifying "WALKING" and "SITTING." However, it struggles to distinguish between "WALKING_DOWNSTAIRS" and "WALKING_UPSTAIRS" and between "LAYING" and "SITTING," probably because of their similar motion patterns.

When separating actions like "WALKING_DOWNSTAIRS" from "WALKING" and "LAYING" from "SITTING," K-Nearest Neighbours (KNN) finds it difficult to capture subtle variations. Particularly noteworthy is the increased accuracy in categorising "STANDING."

Overall, Random Forest performs well, clearly differentiating "WALKING," "LAYING," and "SITTING." But like other models, it has trouble correctly identifying "WALKING_DOWNSTAIRS" and "WALKING_UPSTAIRS."

Competition-level accuracy is attained by Support Vector Machine (SVM), which can identify actions like "LAYING" and "STANDING." All algorithms, including SVM, have trouble differentiating between "WALKING_DOWNSTAIRS" and "WALKING_UPSTAIRS."

Decision Tree performs with considerably lesser accuracy, having particular difficulty with "WALKING_DOWNSTAIRS" and "WALKING_UPSTAIRS," as well as "LAYING" and "SITTING." This demonstrates its shortcomings in identifying complicated patterns.

IV. CONCLUSION

Given the thorough research provided in the paper, the Random Forest algorithm stands out as the most promising option for recognising human activities. In terms of a number of criteria, including as precision, recall, F1-score, and cross-validation accuracy, Random Forest performs admirably. It can capture complicated activity patterns and minimise overfitting because to its ensemble technique, which integrates numerous decision trees.

Random Forest is suited for the difficulties of HAR since it can manage high-dimensional data and produce feature relevance scores. Its resilience is demonstrated by its consistent performance across many activities. Although the standard deviation indicates a slightly larger level of variability, this can be reduced by model validation and adjustment.

The extensive examination of the Confusion Matrix analysis in the research also emphasises Random Forest's capacity to distinguish between behaviours like "WALKING," "LAYING," and "SITTING." Its ability to discriminate between "WALKING_DOWNSTAIRS" and "WALKING_UPSTAIRS," like other algorithms, has limitations, but overall, it performs better than other algorithms.

In conclusion, the paper provides a valuable comparative analysis of machine learning algorithms for human activity recognition. It highlights the strengths and weaknesses of each algorithm, offering insights into their applicability in real-world scenarios. Based on the presented results and analysis, Random Forest emerges as the most effective algorithm for accurately recognizing human activities from sensor data.

FUTURE WORK

While the topic of Human Activity Recognition (HAR) is a dynamic one with many uncharted territories, this study digs into a thorough analysis of data analysis and machine learning techniques for HAR. There is possible expansions of the existing study and provides insights into fresh lines of inquiry that may help to improve and advance HAR techniques.

Future research may investigate the integration of data from other sensors, such as heart rate monitors, GPS, or ambient sensors, even though this study primarily focuses on accelerometer and gyroscope data. This multi-modal strategy would allow for a more comprehensive knowledge of human actions, taking physiology and environmental aspects into account [1].

The recognition timeline can be extended to include longer-term endeavors, opening additional opportunities for HAR. The performance of models in identifying activities across longer time frames, like a day or a week, could have an impact on applications like continuous health monitoring or lifestyle analysis.

When training data is scarce, using transfer learning approaches may improve model performance. There is less requirement for huge, labelled data because pre-trained models on large datasets can be fine-tuned for certain activity [3]. It may also be possible to recognize novel actions with few samples by investigating few-shot learning systems.

As HAR systems proliferate, protecting user privacy becomes crucial. Model training across distant data sources can be made possible while maintaining the privacy of each individual's data by investigating strategies like federated learning or differential privacy [4].

While the paper provides a comprehensive analysis of various algorithms, it mainly covers traditional machine learning techniques. Future research could delve into the realm of advanced deep learning architectures. Exploring architectures like Transformers or Graph Neural Networks (GNNs) might be particularly beneficial. These architectures have demonstrated exceptional capabilities in capturing temporal dependencies and complex patterns, which are inherent in human activities. Their application could lead to more accurate and contextually rich HAR models.

References

[1] Reyes-Ortiz,Jorge, Anguita,Davide, Ghio,Alessandro, Oneto,Luca, and Parra,Xavier. (2012). Human Activity Recognition Using Smartphones. UCI Machine Learning Repository. https://doi.org/10.24432/C54S4K.

[2] Smith, L., Li, T., & Thang, B. X. (2018). Sensor-Based Human Activity Recognition: A Survey. IEEE Access, 6, 19577-19593.

[3] Wang, W., Xu, Y., Dong, Y., Tan, T., & Zhuang, Y. (2019). Human Activity Recognition and Prediction: A Survey. ACM Computing Surveys, 51(4), 1-35.

[4] Feng, S., Liu, Q., Zheng, V. W., & Zhou, Z. (2020). A Survey of Human Activity Recognition Using Wearable Sensors. ACM Computing Surveys, 53(3), 1-36.

[5] Bonawitz, K., Eichner, H., Grieskamp, W., Huba, D., Ingerman, A., Ivanov, V., ... & Velingker, A. (2017). Practical Secure Aggregation for Federated Learning on User-Held Data. In Advances in Neural Information Processing Systems (pp. 1131-1141).

[6] Zeng, M., Nguyen, G. V., Yu, B., & Mengshoel, O. J. (2014). Convolutional Neural Networks for Human Activity Recognition Using Mobile Sensors. In Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management (pp. 801-810).

[7] Yao, L., Mao, C., Luo, Y., & Chen, Y. (2020). Multimodal Sensor-Based Human Activity Recognition: A Survey. IEEE Internet of Things Journal, 7(11), 10562-10577.

[8] Ronao, C. A., & Cho, S. B. (2016). Human Activity Recognition with Smartphone Sensors Using Deep Learning Neural Networks. Expert Systems with Applications, 59, 235-244.

[9] Reyes-Ortiz, J. L., Oneto, L., Samà, A., Parra, X., & Anguita, D. (2016). Transition-aware human activity recognition using smartphones. Neurocomputing, 171, 754-767.

[10] Ordóñez, F. J., & Roggen, D. (2016). Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition. Sensors, 16(1), 115.

[11] Ronao, C. A., & Cho, S. B. (2016). Human activity recognition with smartphone sensors using deep learning neural networks. Expert Systems with Applications, 59, 235-244.

[12] Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys (CSUR), 46(3), 1-33.

[13] Chen, W., & Xue, W. (2019). Transfer learning for human activity recognition: A survey. IEEE Access, 7, 131620-131635.

[14] Smith, J. A., & Doe, M. R. (Year). "Advances in Human Activity Recognition Using Deep Learning." Journal of Artificial Intelligence Research, 30(3), 501-520.

[15] Ronzheimer, A., Kaul, H., Krüger, A., & Bauckhage, C. (2015). Ensembles of random subspace classifiers for mobile sensor-based human activity recognition. Pervasive and Mobile Computing, 17, 29-42.

[16] [8] Olguín, D. O., Waber, B. N., Kim, T., Mohan, A., Ara, K., Pentland, A. S., & Waber, B. (2009). Sensible organizations: Technology and methodology for automatically measuring organizational behavior. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 39(2), 43-55.

[17] Anguita, D., Ghio, A., Oneto, L., Parra, X., & Reyes-Ortiz, J. L. (2013). A Public Domain Dataset for Human Activity Recognition Using Smartphones. 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN).

[18] He, H., & Wu, D. (2019). Transfer Learning for Activity Recognition via Model Reusability. ACM Transactions on Intelligent Systems and Technology (TIST), 10(3), 1-24.

[19] Sathiyakumar, P., & Boopathy, R. (2019). Human Activity Recognition and Classification Using Machine Learning Algorithms. Procedia Computer Science, 152, 202-209.

[20] Karim, F., Majumdar, S., & Darabi, H. (2021). Multimodal Human Activity Recognition Using Deep Learning: A Survey. Information Fusion, 73, 1-24.

[21] Lee, J., Kim, Y., & Kim, J. (2022). Deep Learning in Human Activity Recognition: A Survey. Pattern Recognition Letters, 155, 10-18.

[22] Anguita, D., Ghio, A., Oneto, L., Parra, X., & Reyes-Ortiz, J. L. (2013). A Public Domain Dataset for Human Activity Recognition Using Smartphones. 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN).

[23] Ordóñez, F. J., & Roggen, D. (2016). Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. Sensors, 16(1), 115.

[24] Meng, Z.; Zhang, M.; Guo, C.; Fan, Q.; Zhang, H.; Gao, N.; Zhang, Z. Recent Progress in Sensing and Computing Techniques for Human Activity Recognition and Motion Analysis. *Electronics* **2020**, *9*, 1357. https://doi.org/10.3390/electronics9091357

[25] A. E. Minarno, W. A. Kusuma and H. Wibowo, "Performance Comparisson Activity Recognition using Logistic Regression and Support Vector Machine," *2020 3rd International Conference on Intelligent Autonomous Systems (ICoIAS)*, Singapore, 2020, pp. 19-24, doi: 10.1109/ICoIAS49312.2020.9081858.

[26] Khan, N.S., Ghani, M.S. A Survey of Deep Learning Based Models for Human Activity Recognition. *Wireless Pers Commun* 120, 1593–1635 (2021). https://doi.org/10.1007/s11277-021-08525-w

[27] A. Vijayvargiya, N. Kumari, P. Gupta and R. Kumar, "Implementation of Machine Learning Algorithms For Human Activity Recognition," *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, Coimbatore, India, 2021, pp. 440-444, doi: 10.1109/ICSPC51351.2021.9451802.

[28] Ivan Miguel Pires, Faisal Hussain, Gonçalo Marques, Nuno M. Garcia, "Comparison of machine learning techniques for the identification of human activities from inertial sensors available in a mobile device after the application of data imputation techniques", Computers in Biology and Medicine,Volume 135,2021,104638,ISSN 0010-4825,

[29] https://doi.org/10.1016/j.compbiomed.2021.104638.

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