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ACTIVE MACHINE LEARNING FOR HETEROGENEITY ACTIVITY RECOGNITION THROUGH SMARTWATCH SENSORS

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Abstract : The proliferation of wearable technology, particularly smartwatches, has provided a rich source of data for activity recognition. This paper explores the application of active machine learning techniques to recognize heterogeneous activities through smartwatch sensors. The proposed system leverages accelerometer and gyroscope data to classify various physical activities such as walking, running, biking, and standing, among others. Active learning is utilized to enhance the model's performance by selectively querying the most informative data points, thus minimizing the amount of labeled data required. The methodology involves initial training with a small labeled dataset, followed by iterative cycles of active learning to refine the model. Experimental results demonstrate that the proposed approach achieves high accuracy and robustness in activity recognition, outperforming traditional machine learning methods. This study underscores the potential of active learning in reducing the labeling effort while maintaining high classification accuracy, making it a viable solution for real-time activity monitoring in ubiquitous healthcare and fitness applications

IndexTerms **-** Active Machine Learning, Activity Recognition, Smartwatch Sensors, Wearable Technology, Accelerometer, Gyroscope, Data Classification, Real-time Monitoring, Ubiquitous Healthcare, Fitness Applications

I. INTRODUCTION:

Heterogeneity activity recognition understands the human physical activities which analyses and record by digital devices using the smart sensors. It recognizes activities and health conditions and respond with respective results. This accurately recognizing a wide range of physical activities using these devices remains a complex challenge. Traditional machine learning methods often struggle with the heterogeneous nature of activities and require large labelled datasets, hindering real-time application in healthcare and fitness. The study focuses on leveraging accelerometer and gyroscope data to classify common physical activities such as walking, running, biking, and standing. These technologies enable proactive health management, potentially decreasing the strain on healthcare and provide timely health recommendations.

The primary objective of this project is to develop a robust and efficient activity recognition system using smartwatch sensors, leveraging active machine learning to handle the heterogeneity in user data.

EXISTING SYSTEM:

In heterogeneity activity recognition methods typically involve training models on labelled datasets comprising accelerometer and gyroscope data to classify various physical activities. This paper is an significance approach of human activities through traditional machine learning algorithms such as Random Forest, XGBoost, Decision Tree, K-Nearest Neighbors, Gradient Boosting, and LightGBM have been widely used for activity recognition using smartwatch sensors. RF and DT are popular due to their simplicity and interpretability, while KNN provides a non-parametric approach that can adapt to various data distributions. XGBoost, GB, and LGBM are gradient boosting techniques that enhance prediction accuracy by combining multiple weak learners. Although these algorithms achieve high accuracy, they require substantial amounts of labelled data and do not efficiently handle heterogeneous activity recognition. Active machine learning addresses this limitation by iteratively selecting the most informative data points, thereby reducing the labeling effort while maintaining robust performance.

1.1.1 CHALLENGES:

In heterogeneity activity recognition we acquire rational decisions as the provided output data through the smartwatches are less accurate than other monitoring tools like radar, camera etc. The occurrence of several challenges need to reduced in providing the accurate results.

Model complexity:

Complex models like GB and LightGBM can be difficult to interpret.

Computationally Intensive:
Some algorithms (e.g., XGBoost, GB) can be computationally expensive and slow, particularly on large dataset

Inaccurate:
More complicity in providing accurate results where this approach provides results of the performance with noisy or irrelevant sensor data

1.2 PROPOSED SYSTEMS

The proposed system for heterogeneity activity recognition through smartwatch sensors incorporates advanced active machine learning techniques to classify diverse physical activities. The system leverages K-best feature selection and a stacking classifier to optimize performance. Initially, accelerometer and gyroscope data from smartwatches are collected and preprocessed. K-best feature selection is employed to identify the most relevant features, enhancing the model's accuracy. The stacking classifier combines multiple base classifiers to improve prediction robustness and accuracy. The system begins with a small labeled dataset for initial training. Active learning iteratively refines the model by selectively querying the most informative data points, reducing the labeling effort. This approach ensures that the model remains adaptive and efficient in recognizing a variety of activities with minimal data annotation.

Advantages:

High accuracy:

Achieves superior classification accuracy through optimal feature selection and ensemble learning.

Robust Performance:
Combines multiple classifiers to enhance prediction reliability and handle heterogeneous activities effectively

Real-time Monitoring:
Enables efficient real-time activity recognition, suitable for ubiquitous healthcare and fitness applications

II.LITERATURE SURVEY:

Heterogeneity activity recognition is explored activity recognition using multiple sensors including accelerometers and gyroscopes. Demonstrated improved accuracy by integrating data from different body positions. Highlighted the effectiveness of multi-sensor fusion for robust activity monitoring. Identified challenges such as sensor calibration, data synchronization, and the need for sophisticated algorithms to handle multi-sensor data street effectively. Concluded that integrating sensor data from multiple body positions enhances the reliability and accuracy of activity recognition systems, making them suitable for real-world applications in healthcare, sports performance analysis, and human-computer interaction. Developed algorithms to recognize activities using acceleration data annotated by users. Compared various feature extraction methods for classifying dynamic activities from accelerometer data. Identified optimal features for distinguishing between different activities such as walking, running, and cycling. Provided insights into selecting effective features to enhance activity recognition performance. Provided a comprehensive survey of human activity recognition using wearable sensors. Reviewed various techniques and algorithms applied to sensor data for activity recognition. Summarized outcomes and trends in the field, emphasizing the evolution towards more accurate and robust activity recognition systems.

III.METHODOLOGY:

3.1 INPUT:

Heterogeneity activity recognition, the initial process is need to register with the details and once the registration is successful then it reflects to login page. Now need to login with the details. Once its logged in successfully the model page will be reflected, need to select the model types that and its provide the information of how accurate the model will provide results. The accaurcy varies to various models. In the prediction page, the ranges of values for input [0 to 20]. Based in the input values it will recognise the type of activity performing.

3.2 OUTPUT:

The highest results achieved were 99.99% from RF and DT on the gyroscope dataset, and on the accelerometer dataset, they were 99.98% with RF. The other models on the gyroscope,

including XG-Boost, KNN, GB, and LGBM, provided an accuracy of98.14%, 99.26%, 94.79% and 98.18%, and F1-score of98.14%, 99.26%, 94.76% and 98.18% respectively. Mean-while, on the accelerometer, other models, including DT, XGBoost, KNN, GB, and LGBM, provided an accuracy of 99.97%, 98.26%, 99.35%, 94.26 and 98.30% respectively.

Output screens:

Registration Page:

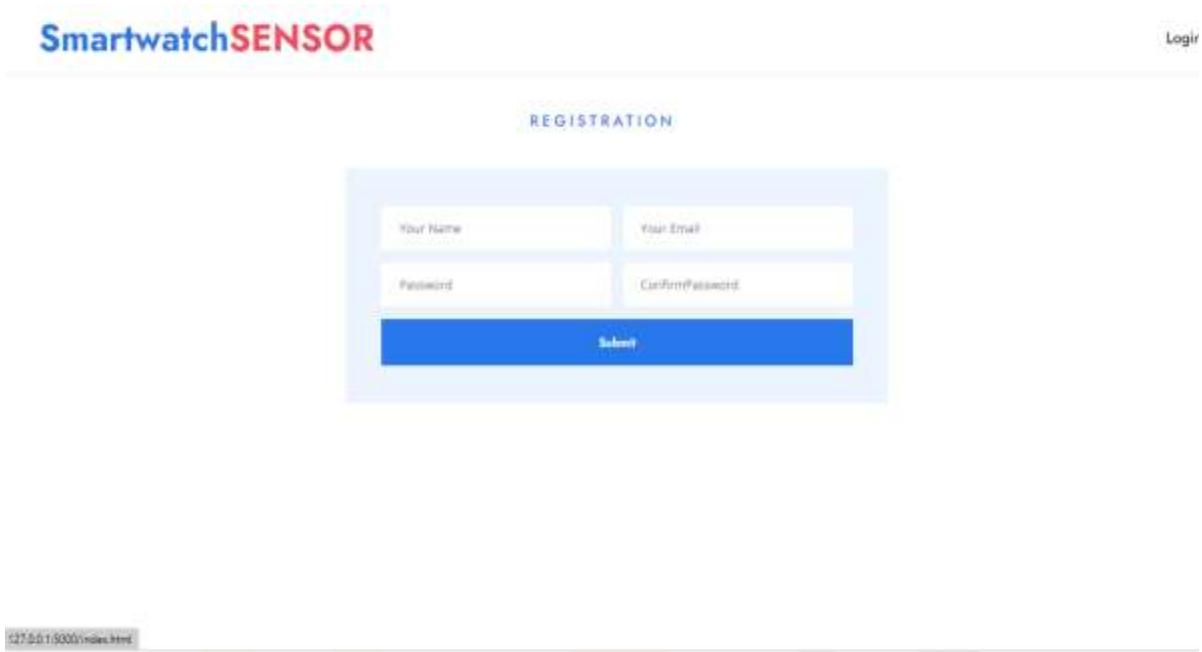

Fig. 3.2.1

Login Page:

Fig. 3.2.2

Model Page:

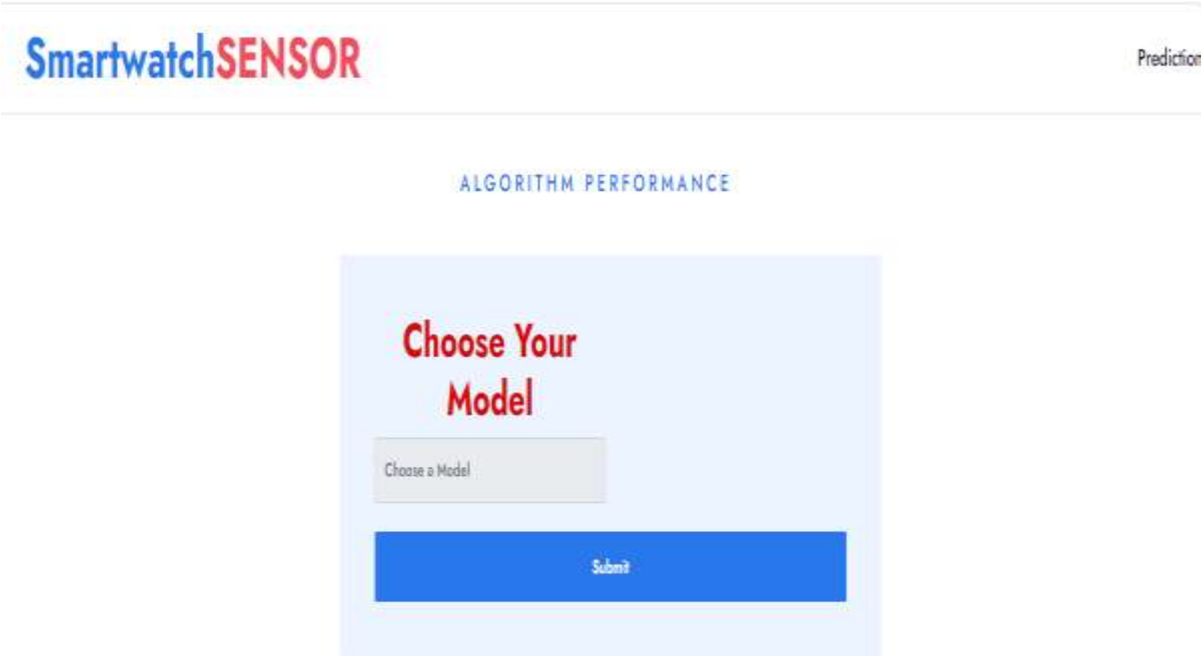

Fig. 3.2.3

Prediction Page:

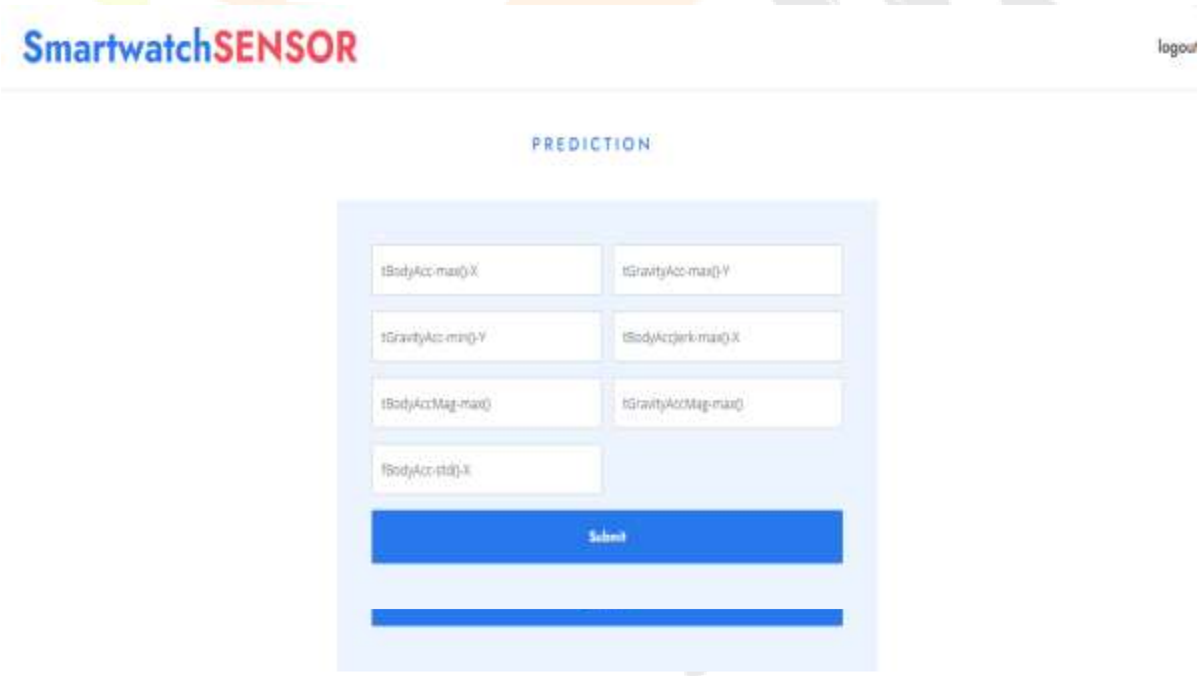

Fig. 3.2.4

Fig. 3.2.5

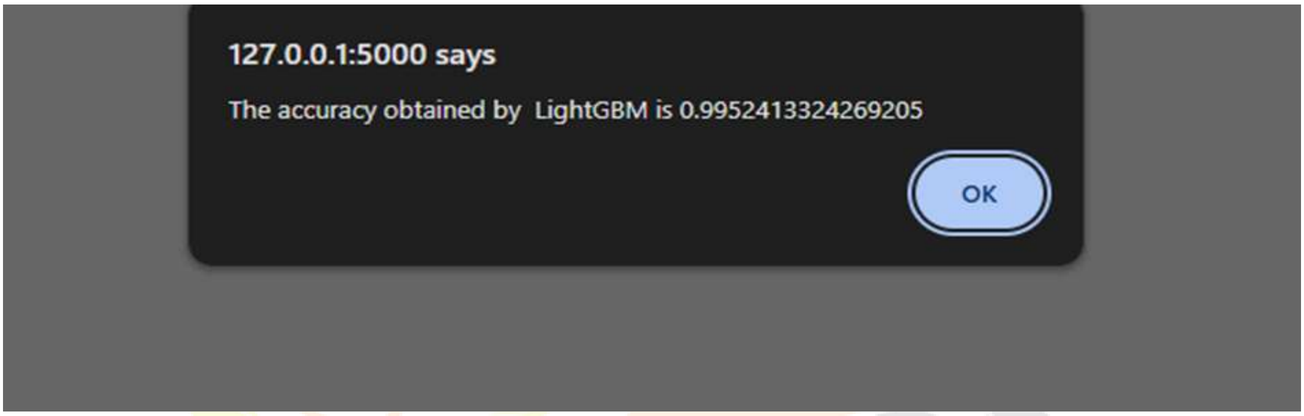

Fig. 3.2.6

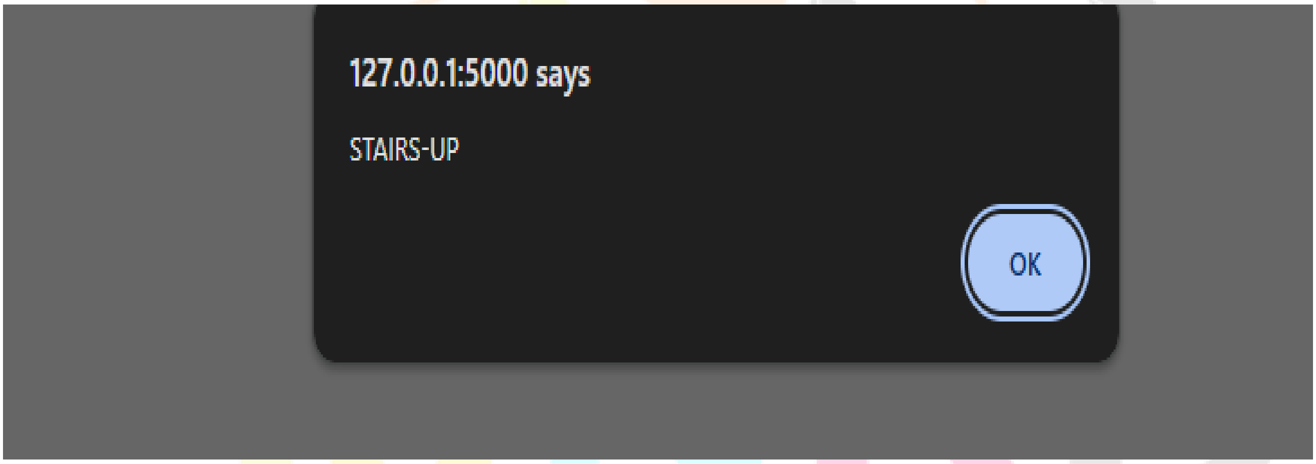

Fig. 3.2.7

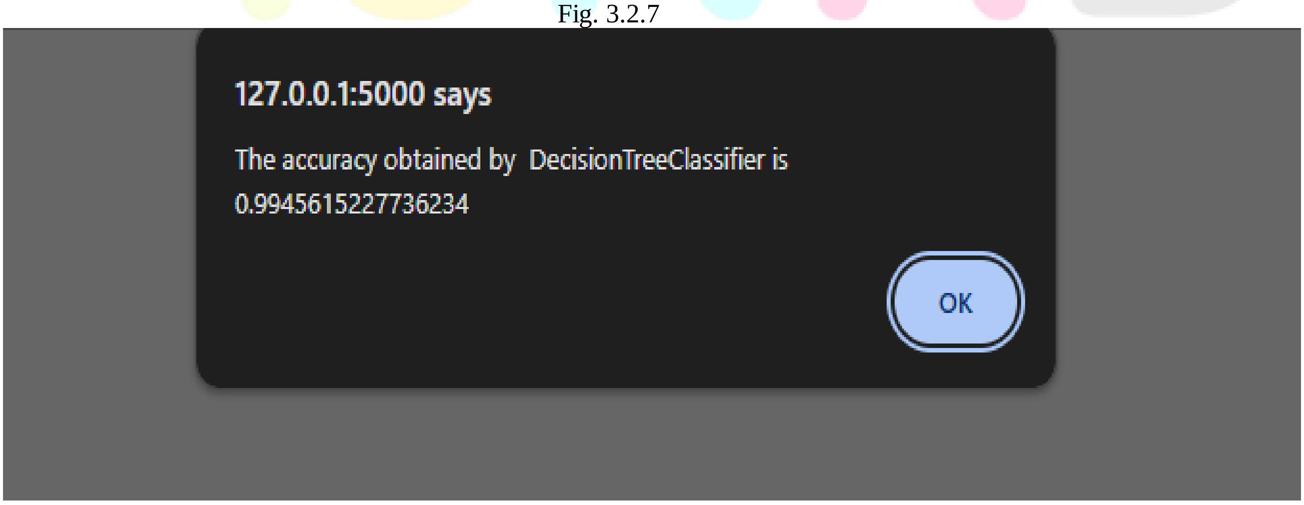

Fig. 3.2.8

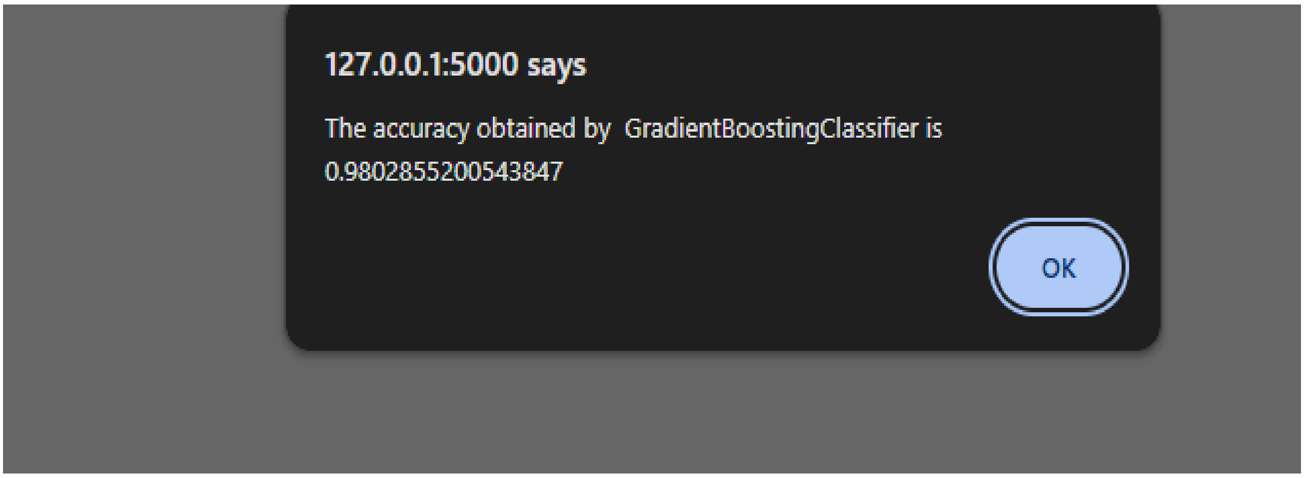

Fig. 3.2.9

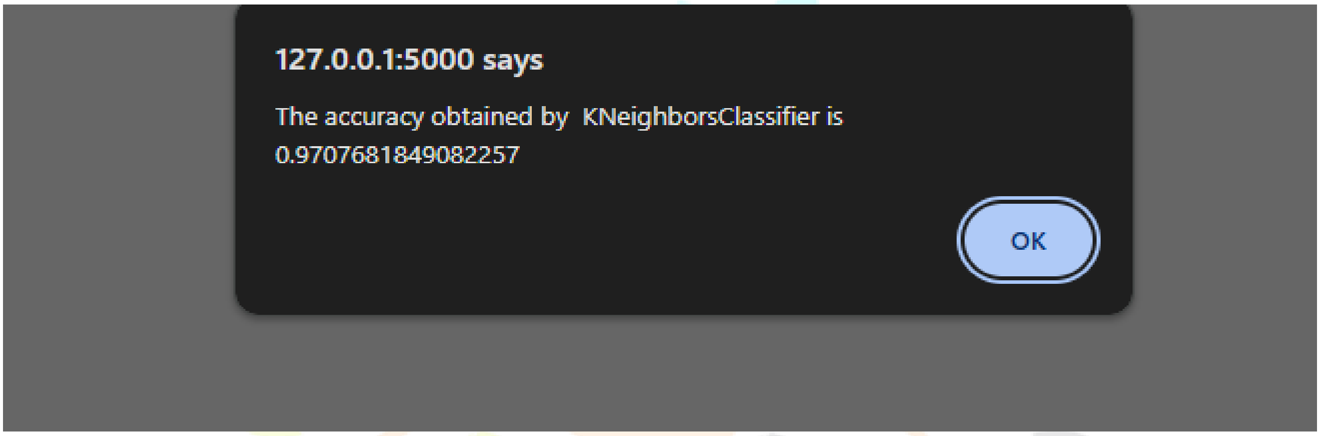

Fig. 3.2.10

IV.RESULTS:
The system begins with users interacting through either a web application. On the web application, users enter their login credentials and if they are new user need to register in the website. This data is securely processed and stored. The accelerometer and gyroscope data collected from smartwatch sensors serve as input features to the various models like Random forest, XGboost, Decision tree, K-nearest neighbours, Gradient Boosting, Light Gradient Boosting Machine, Stacking classifier. The activity will be recognised based on the prediction through the sensors. The application provides real-time activity performing through the smart watch sensors.

V.DISCUSSIONS:
Heterogeneity activity recognition is mainly used for recognising the activity performed. It used the accelerometer and gyroscope data collected from smartwatch sensors serve as input features to the various models like Random forest, XGboost, Decision tree, K-nearest neighbours, Gradient Boosting, Light Gradient Boosting Machine, Stacking classifier. Here are some key areas for the future scope of this project,

1. **Multi-Modal Sensor Fusion**: Integrate data from multiple sensors (e.g., accelerometer, gyroscope, heart rate monitor) to improve accuracy and robustness of activity recognition.

2. **Incremental Learning:** Implement techniques that allow the model to learn continuously from new data without retraining from scratch, adapting to user-specific behaviors over time.

3. **Personalization:** Develop personalized activity models that adapt to individual user habits, preferences, and physical conditions for more accurate recognition.

4. **Real-Time Feedback:** Provide real-time feedback to users based on their activity patterns, encouraging healthier behaviours or providing alerts for potential health risks.

5. **Integration with Health Systems**: Integrate with electronic health records or health monitoring systems to provide comprehensive health insights based on activity data.

6. **Scalability Solutions**: As the number of activities performed increases, ensuring the system can scale efficiently will be essential. It maintain performance and provide accurate results.

VI.CONCLUSION:

In conclusion, this study explores the application of hybrid machine learning techniques to enhance bankruptcy forecasting using an unbalanced Polish dataset. By leveraging a combination of methods such as ensemble learning, feature selection. Our findings demonstrate that the ensemble of classifiers, including Random Forest, Gradient Boosting, and SVM, significantly improves predictive accuracy and robustness compared to individual models. Feature selection methods such as L1-SVM and Recursive Feature Elimination provided insights into critical predictors of bankruptcy risk. These advancements contribute to more reliable bankruptcy forecasting models, offering valuable insights for financial institutions and regulatory bodies in managing risks effectively. Future research should focus on refining model interpretability and scalability across diverse financial environments to further validate the efficacy of hybrid machine learning approaches in financial forecasting tasks.

VII.ACKNOWLEDGEMENT

M. Satish is an enthusiastic and committed faculty member in the Department of Computer Science. As an early-career academician, he has shown strong dedication to student development through active involvement in project guidance and technical mentoring. Despite being at the beginning of his professional journey, he has effectively guided students in executing academic projects with precision and conceptual clarity. His passion for teaching, coupled with a solid understanding of core computer science principles, positions him as a promising educator and mentor. He continues to contribute meaningfully to the academic environment through his proactive approach to learning and student engagement.

Kakkirala Srikanth is pursuing his final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Machine learning Kakkirala Srikanth has taken up his PG project Active machine learning for heterogeneity activity recognition through smartwatch sensors and published the paper in connection to the project under the guidance of M. Satish, Assistant Professor, Master of Computer Applications, SVPEC.

VIII.REFERENCES:

1. https://ieeexplore.ieee.org/document/9734546
2. https://www.esann.org/sites/default/files/proceedings/legacy/es2013-84.pdf
3. https://www.mdpi.com/1424-8220/20/9/2556
4. https://www.mdpi.com/1424-8220/10/2/1154
5. https://www.mdpi.com/1424-8220/18/8/2452
6. https://ieeexplore.ieee.org/document/7471417
7. https://www.mdpi.com/1424-8220/21/22/7485
8. https://dl.acm.org/doi/10.1145/1964897.1964918
9. https://iopscience.iop.org/article/10.1088/0967-3334/30/4/R1
10. https://ieeexplore.ieee.org/document/6312303
11. https://www.sciencedirect.com/science/article/pii/S0167739X15002577
12. https://www.mdpi.com/1424-8220/14/12/2622
13. https://www.sciencedirect.com/science/article/pii/S0925231220307071
14. https://ieeexplore.ieee.org/document/6221187
15. https://www.sciencedirect.com/science/article/pii/S1440244014001053
16. https://www.mdpi.com/1424-8220/16/1/115
17. https://www.sciencedirect.com/science/article/pii/S0166361509000806
18. https://dl.acm.org/doi/10.1145/2750858.2804288
19. https://link.springer.com/chapter/10.1007/978-3-540-24607-6_2
20. https://dl.acm.org/doi/10.4108/eai.10-10-2019.2299739