Journal of Robotics and Control (JRC)
Volume 5, Issue 5, 2024
ISSN: 2715-5072, DOI: 10.18196/jrc.v5i5.22443

Human Activity Recognition Using Accelerometer & Gyroscope Smartphone Sensor by Extract Statistical Features

Muthana Hmod Abdullah [1*], M. A. Ahmed [2]
[1, 2] Department of Computer Science, Faculty of Computers & Mathematics, Tikrit University, Tikrit
Email: [1] muthana.h.abdullah@st.tu.edu.iq, [2] mohamed.aktham@tu.edu.iq
*Corresponding Author

***Abstract*—Understanding behavioral patterns and forecasting the bodily motions of persons heavily relies on detecting human activities. This has profound ramifications in several domains, including healthcare, sports, and security. This study sought to identify and classify 18 human actions recorded by 90 people using smartphone sensors using the KU-HAR dataset. The primary aim of this study is to examine statistical features such as (mean, mod, entropy, max, median …etc.) derived from time-domain sensory data collected using accelerometers and gyroscopes. Activity detection utilizes many machine learning methods such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic Regression (LG), Naïve Bayes (NB), and AdaBoost. The RF model achieves the highest overall accuracy of 99%. While the DT model gets 95%, SVM receives 93%, and the KNN gets 82%. At the same time, the other model didn't get good results. The research is evaluated using accuracy, recall, precision, and f1-scor. The research contribution is to extract the statistical feature from the raw file of the sensor to create a new dataset. This research recommends employing statistical features in time series. Future research is recommended to solve misclassification in certain activities, which could be achieved using feature selection to reduce the number of features.**

Keywords—Human Activity; Classification Algorithms; Wearable Sensor; Tsfresh; Statistical Feature.

I. INTRODUCTION

There is a growing need to improve the living conditions of elderly individuals [1] by using technology and artificial intelligence to tackle cognitive and physical disabilities [2], guarantee safety [3], and aid in daily living activities (ADL) [4]. Human Activity Recognition (HAR) uses sensor technologies to anticipate and categorize human behaviors [5]. HAR is important in this effort [6]. Human Activity Recognition (HAR) can accurately recognize and classify daily activities using smartphone data from accelerometers and gyroscopes [7]. This technology is valuable for monitoring and enhancing individual health and lifestyle trends [8]. Nevertheless, deriving significant insights from this data is difficult owing to its intricate nature [9]. This project aims to enhance Human Activity Recognition (HAR) by creating new datasets and employing a range of machine learning and deep learning algorithms [10]. The goal is to obtain higher levels of precision and dependability in recognizing activities, which is crucial for healthcare applications, geriatric monitoring, and other related domains [11].

Numerous applications in healthcare [12] Stand to benefit in the present day from developments in wireless networking technology [13], peripheral devices [14], information and communication technology [15], and smartphones [16]These developments facilitate examining large-scale patient data, medical images, recordings, and images using data mining technologies. Moreover, these technologies enable the identification of human activity in daily life routines. [17].

Activity is the motion of the body or the part of it with time and gravity [18, 19]. Human Activity Recognition (HAR) is a classification project that entails the categorization of an individual's activity through the utilization of data acquired from various sources, such as sensors [20] and cameras [21] , The healthcare industry extensively utilizes it for many purposes, namely in the ongoing surveillance of activities and identification of falls in elderly individuals [22]. Furthermore, it exhibits considerable promise in enabling the advancement of many applications, including indoor localization [23], augmented reality [24], and the Internet of Things (IoT) [25], inside intelligent building control systems[26]. These applications aim to deliver a comfortable environment while maintaining high efficiency of energy [27] [28]. HAR is divided into two approaches: vision-based and sensor-based.

In vision-based human activity recognition [29], the objective is to predict actions [30], activities [31], or movements by utilizing visual data obtained from cameras [32], consisting of photos or videos [33]. The process entails examining video frames or photographs to comprehend and analyze human motions. [34], gestures [35], and behaviors [36]. The researchers prioritize the improvement of recognition accuracy and efficiency by the extraction of significant characteristics from visual input, as seen in Fig. 1. Vision-based methods for recognizing human activity have several advantages [37], such as capturing detailed information [38], being non-intrusive [39], having wide-ranging applications [40], being scalable [41], adaptable to changing environments [42], and combining several modes of data [43]. Nevertheless, it has challenges such as safeguarding privacy [44], optimizing resource use [45], and addressing blind spots [46].

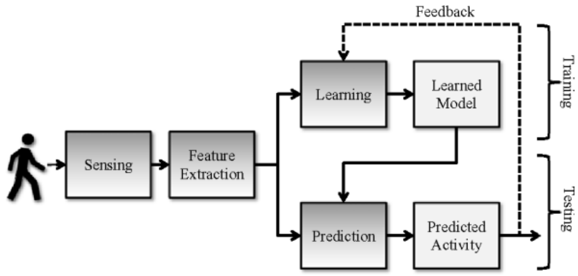

Fig. 1. Process of human recognition

Sensor-based human activity detection involves using many sensor types, including accelerometers, gyroscopes, and magnetometers, to gather data about motion, orientation, and physiological signals [47]. The sensory data collected is analyzed to identify and categorize particular activities or behaviors exhibited by individuals. Sensor-based researchers employ a range of devices [48]. They are outfitted with sensors, including glasses [49], cellphones [50], watches [51], wristbands [52], chest patches [53], and shoes refer to Fig. 2. [46]. Sensors such as accelerometers, gyroscopes, proximity sensors, and magnetometers are included in cell phones. The utilization of these sensors enables the measurement of our physical activity [54]. An accelerometer is a device that measures the change in velocity of an object over time or a body at rest, while a gyroscope can detect movements that are difficult for humans to perceive, such as rotation and changes in orientation [55]. The proliferation of apps and computing capabilities has led to a notable surge in the popularity of smartphones in recent years [56].

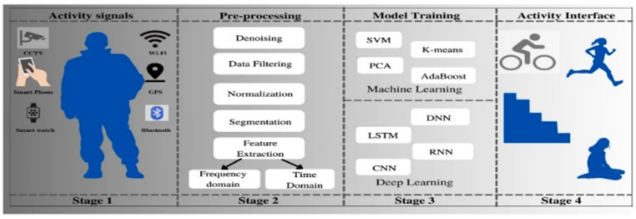

Fig. 2. Sensors position

Sensor-based methodologies have several benefits. They enable the collection of data at any location and moment and can offer information tailored to the user [57]. The proliferation of commercially available wearable gadgets has led to significant growth [58]. The problem of varying measuring conditions, including the type of device [59], possession method, wearing technique, and measurement application continue to exist. The conditions above may exhibit variability across users and different measurement dates [60].

In this research, machine learning algorithms are used along with the KU_HAR dataset to recognize human activity. The KU_HAR dataset comprises data on 18 distinct activities obtained from 90 participants, 75 males and 15 females. The data was gathered utilizing sensors embedded in smartphones., specifically the Accelerometer and Gyroscope; we will describe more detail in the methodology section [55]. This dataset is available on the Kaggle website, and there are a few studies on it, but no one uses extracted statistical features from it. Statistical features are extracted from raw data in the KU_HAR dataset. To recognize human activity using machine learning algorithms like "Random Forest" algorithm (RF), Decision Tree algorithm (DT), "Support Vector Machine" algorithm (SVM), K-Nearest Neighbor (KNN), Logistic Regression (LG), Naïve Bayes (NB), and AdaBoost.

The research contribution is:

- Develop an intelligent model using a mobile inertial sensor to recognize human activity.
- By extracting statistical features from the sensor's raw file, create a new dataset different from the original in size, sample rate, and features.
- Obtain high accuracy during training and validation.

The rest of the study unfolds as follows: section (III) describes the previous studies on HAR that are helpful to understanding the related work to the research, section (IV) describes the research methodology that is applied to the research dataset, including the data collection, preprocessing, Data balance, Model evaluation, and confusion metrics, and section (V) presents the results and discussion of the study. Lastly, section (VII) serves as the conclusion, summarizing the most important discoveries and outlining potential directions for further research to develop the HAR field.

II. LITERATURE REVIEW

The scholarly literature about HAR has garnered significant academic interest in recent times. Multiple research has concentrated on identifying diverse behaviors through mobile sensors. Researchers undertook a series of studies exploring different approaches and tactics for Human Activity Recognition (HAR) to characterize human actions using sensor data accurately.

In [55] The author compiled the KU-HAR dataset using a mobile sensor. The dataset has 18 distinct categories collected from 90 individuals, with 20,750 sub-samples. The author implemented the Random Forest method and achieved a 90% accuracy rate. The study dataset is utilized in our suggested work. The dataset is vast, with several individuals involved in its collection in 2021. It encompasses 18 distinct classifications.

In [61] The author categorizes six human activity recognition (HAR) activities: standing, sitting, descending stairs, ascending stairs, lying down, and walking. The author used a dataset from a smartphone's accelerometer and gyroscope sensors and applied machine learning and deep learning techniques to analyze the data. After extracting 561 features, the 1DCNN and SVM models obtained superior results, with a 96% accuracy rate.

In [62], The author introduces a feature fusion system that combines manually crafted and automatically obtained features using a deep learning method for Human Activity Recognition (HAR). The author has devised a Maximum Full a Posterior (MFAP) approach to enhance the effectiveness of HAR, taking into account common human behavioral tendencies. The experimental findings indicate that the proposed methodology surpasses the most advanced techniques in a publicly available dataset and a dataset collected by the author.

In [26] The author suggests integrating residual structure and layer normalization into a bidirectional long-short-term memory network (BLSTM). This integration will expand the capabilities of extracting features and improve the stability and accuracy of recognizing activities. The author assessed the model's performance by conducting tests on the KU-HAR dataset, resulting in a 97% accuracy rate.

In [63] The author proposed an architecture called DeepCNN-RF, which integrates a convolutional neural network (CNN) with a random forest classifier to introduce unpredictability into the model. The suggested models have been tested using publically available HAR Datasets, such as UCI HAR and WISDM Dataset. The experimental results demonstrate that the hybrid models outperform the most sophisticated data mining and machine learning methods in UCI HAR and WISDM, obtaining an accuracy of 97.77% and 98.2%, respectively.

In [64] The author proposes an all-encompassing activity detection framework that utilizes deep learning by integrating Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM). The CNN-LSTM approach improves the precision of forecasting human actions by examining unprocessed data. Furthermore, it streamlines the model and removes the need for specialist feature engineering. The model exhibits a 99% level of accuracy when evaluated on the iSPL dataset, which is an internal dataset. When evaluated on the UCI HAR public dataset, it achieves an accuracy of 92%.

In [65] The author introduced a one-dimensional convolutional neural network (1D-CNN) model to identify and classify human behavior. He utilized the model on the Motion Sense dataset, which was gathered using a smartphone's accelerometer and gyroscope sensor. After undergoing testing, the model attained a 96% accuracy.

We conduct a comparative analysis of our proposed study with relevant prior research to differentiate it from them. The factors we take into account include the dataset's balance or imbalance, the number of data collectors, the number of classes, the specific sensors used (limited to accelerometer and gyroscope), whether the data is preprocessed, the dataset size, the algorithms applied, the number of features, and the accuracy. Table I shows the compared table.

According to Table I, our suggested study demonstrates significant differences from prior studies. We have achieved much higher accuracy on the KU-HAR dataset than a previous study that utilized the same dataset. In addition, our strategy encompasses both balanced and unbalanced scenarios for training, which is uncommon in prior studies that frequently overlook the need for data balancing. We utilize seven distinct algorithms and extract statistical characteristics to improve the efficiency and resilience of human activity identification.

III. METHODOLOGY

A. *Methodology*

This section provides an overview of the technique utilized in the study, which includes gathering the dataset, preprocessing procedures, and dividing data for training and evaluating the model, as seen in Fig. 3. It also provides a comprehensive overview of each step involved in the suggested technique. The subsequent sequence encompasses the specifics of each step within the proposed methodology.

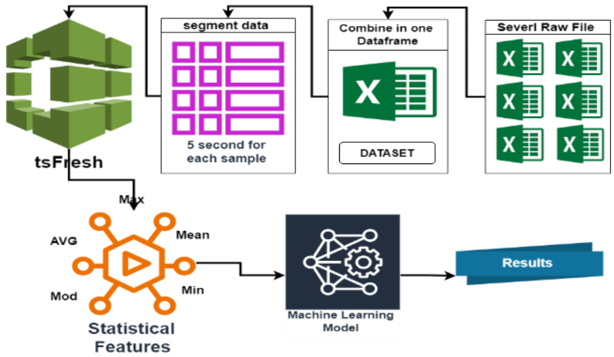

Fig. 3. The proposed steps of the Human Activity

In this paper, we work on the original data of the sensor by extracting statistical features every 5 seconds to create a new dataset that is different from the original one.

TABLE I. COMPARED WITH RELATED WORK

Paper	Dataset name	Balance	No of users	No of classes	Sensor	Preprocessing	Size of dataset	Model	No of Features	Performance
Proposed	KU-HAR	Balance and imbalance	90	18	ACC, GYR	Yes	12448 sample 2808 sample 23562 sample	RF, DT, SVM, KNN, LG, NB, AdaBoost	4698	99%, 78%, 72%
[61]	UCI HAR	imbalance	-	6	ACC, GYR	Yes	10299	1DCNN	561	96.13%
[62]	Private name	imbalance	12	6	ACC, GYR	-	4752	MFAP	-	98.85%
[26]	KU-HAR	imbalance	90	18	ACC, GYR	Yes	20,750	1DCNN-ResBLSTM	-	97.89%
[63]	UCI HAR	imbalance	30	6	ACC, GYR	Yes	10299	CNN+RF	561	98.2%
[64]	UCI HAR	imbalance	30	6	ACC, GYR	Yes	10299	CNN-LSTM	-	92.2%
[65]	MotionSense	Imbalance	24	6	ACC, GYR	Yes	-	1DCNN	-	96.77%

B. Data Collection

The dataset utilized in this study was KU-HAR [55] Which was acquired from a cohort of 90 participants by positioning the phone in a waist bag. In the context of data collection, Fig. 4. depicts the act of carrying a smartphone. The data collected by the smartphone's accelerometer and gyroscope sensors occurred at 100 Hz. The data consists of 18 distinct activities, sitting (1 min), standing (1 min), running 20 meters, walking 20 meters, Talk-sit with hand movements while sitting (1 min), Stand-sit (5 times), descending stairs (≈50 s), Talk-stand with hand movements while standing or walking (1 min), Laying (1 min), transitioning from lying down to standing (5 times), performing push-ups (5 times), jumping (10 times), picking up objects (10 times), sitting up (5 times), walking backward 20 meters, Walk-circle (≈ 20 s), ascending stairs (≈1 min), and engaging in table tennis (1 min). Table II displays the specific information of the KU-HAR dataset.

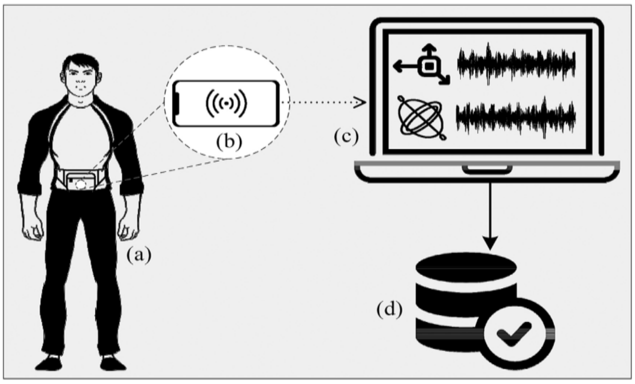

Fig. 4. Position of the smartphone

TABLE II. DETAIL OF THE DATASET

Number of participants:	90
Number of males:	75
Number of females:	15
Range of age:	18 – 34
Age average:	21.7
Range of weight:	42.2
Weight average:	63.2
Preexisting heart conditions:	2

C. Preprocessing

The preprocessing stage involves several key steps, including data cleaning, segmentation of the data, feature extraction, and data splitting. These steps lay the foundation for analyzing and classifying human activities. Data cleaning is the initial step in pre-processing, and it aims to remove redundant data. The data could include a signal without a value, representing the recording activities' start period. Consequently, the KU-HAR dataset was cleaned by eliminating the first millisecond of each sensor signal using a programming code to clean all files of the sensor by examining the first row of the sensor file. If the value is zero or repeated value, then it is removed, because the person did not begin to move. These sensor datasets are subsequently Segmented into "windows" with predefined sampling intervals. Each display contains a tiny window that Denotes the signal received from the sensor. In this study, the windows are segmented into non-overlapping windows with 500 data points, corresponding to 5 seconds for each activity. Fig. 5. show an example of how data is segmented. The red color data will represent a single sample for the activity, and the blue color will represent the second sample of the same activity because this file is for one activity, and the green color is the same; every activity has a different file. Therefore, the labeling process will not be confusing, Fig. 6. shows how the segmented data point is transferred.

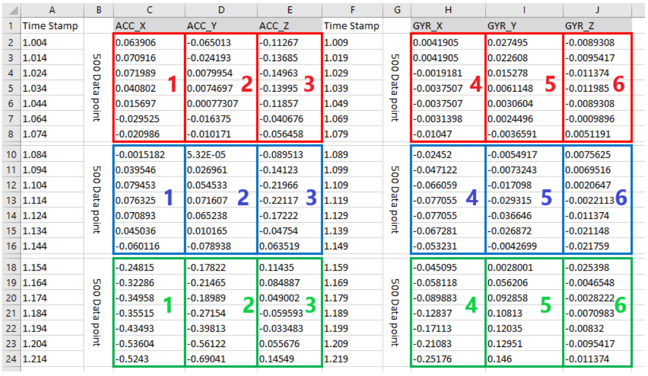

Fig. 5. Segmented raw data

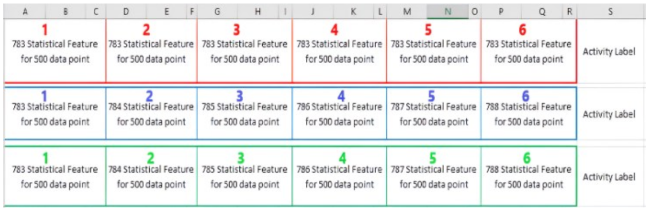

Fig. 6. Feature extracted from segmented data points

Extracting sensor features in time-series data is crucial to train a model effectively. Therefore, the statistical features are extracted from the original file of the collected dataset. In this research, the tsFresh Python package was used to extract features such as maximum, minimum, mean, median, standard deviation, variance, skewness, root mean square, signal energy, number of peaks, peak-to-peak amplitude, interquartile range, absolute area under the curve, zero-crossing rate, autocorrelation, correlation coefficient, entropy, mean absolute deviation, the time between peaks, etc. [66]. This happens by taking the first segment of the first column of the accelerometer, and extract statistical features from it. Then continue to the other column of the same segment. As a result of using tsfresh, 783 features were generated for each segment in the sensor channel, totaling 4698 features and yielding 12448 samples for all activity raw files. Finally, the dataset is split into training and testing sets. The set training constituted 70 % of the dataset, the remaining 30% comprising the testing set.

D. Data Balance

The issue of imbalanced data categorization arises when a significant disparity in the proportional class sizes within a given dataset [67]. It is a straightforward and widely used method to equalize the distribution of classes in the training data. One of the methods used to achieve balance in the original data space is Random Over-sampling (ROS) or Random Under-sampling (RUS) [68]. As shown in Fig. 7.

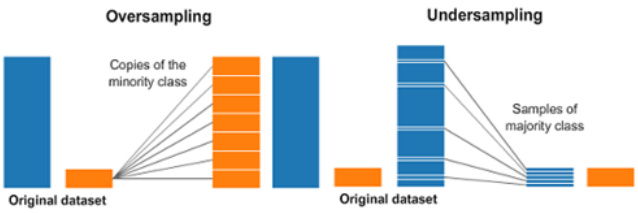

Fig. 7. Over-sampling and Under-sampling methods

In this research, to get the best accuracy results, we train the model in two scenarios, one with an imbalanced dataset and the other with a balanced dataset, by applying both over- and under-sampling methods.

E. Model Evaluation

Several methods, such as a confusion matrix, accuracy, recall, precision, and F-score, may be used to assess a classification model's efficacy. [69]. These metrics are widely employed in academic literature. These indicators aid in evaluating the efficacy of the classification model, pinpointing regions of suboptimal performance [70], and guiding necessary modifications. The methodologies employed in the current investigation are outlined in a comprehensive manner below [71].

F. Confusion Metrics

The confusion matrix is a matrix with dimensions of N by N, which is utilized to evaluate the efficacy of model classification. The variable "N" denotes the aggregate number of target categories in the present context. The matrix facilitates comparing the observed goal values and the machine learning model. Algorithm's anticipated target values [72]. The measurements of the confusion matrix and positive/negative results are shown in Fig. 8.

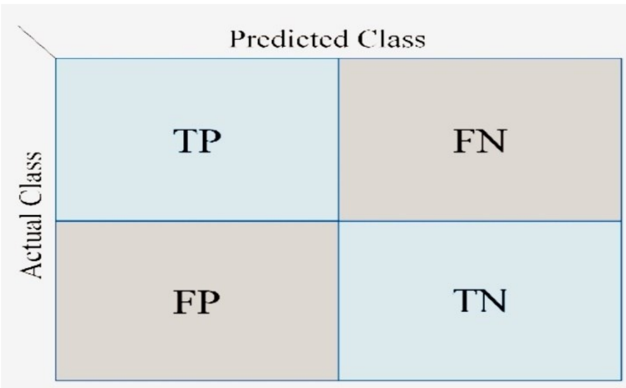

Fig. 8. Confusion metrics

- (**True Positives) (TP)** represents the instances in which a model accurately identifies samples in the positive class [73].
- (**True Negatives) (TN)** are the instances in which the model identifies samples correctly about harmful category [74].
- (**False Positives) (FP)** is the instances where The model misclassified the negative class samples as the positive class [75].
- (**False Negatives) (FN)** represent the positive class values that the model incorrectly classified as the negative class [76].

Recall, also called Sensitivity, inquires about the algorithm's ability to identify all relevant cases correctly. This quantifies the classifier's capacity to recognize positive instances accurately and is referred to as the actual Positive Rate) (TPR) [77].

Precision requires a specific count of errors made in the relevant cases. This refers to the positive predictive value of the classifier, which indicates the accuracy of predictions [78].

The formulas for “precision” and “recall” are presented in Equations (1) and (2).

$$precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Accuracy: Classification accuracy measures the proportion of correct predictions [79].

$$Accuracy = \frac{TP + TN}{Tp + TN + FP + FN} \tag{3}$$

The F-score: known as the f1_score, is a metric that measures the model's precision on a dataset. The F1_score is a standard metric for evaluating models of machine learning. It is a technique that merges the “recall” and “precision” of the model, as described in Equation (4). It is the harmonic range of “precision” and “recall” of the model [80].

$$F1 - scor = \frac{2}{1 \div recall \times 1 \div precision} = 2\frac{precision \times recall}{precision + recall} = \frac{TP}{TP + \frac{1}{2}(FP+FN)} \tag{4}$$

IV. RESULTS

Our model was trained using the Jupyter Notebook environment, namely the Google Collab service, which is free [81]. This service facilitates the provision of computer resources, including 12.7 Gigabyte (GB) system Random Access Memory (RAM), 16 GB GPUs, and more than 78 GB Hard desk for temporary data saving [81]. The aim is to design a model that can accurately recognize human activity using the accelerometer and gyroscope built into smartphones. This is important because smartphones are constantly with people and should not violate their privacy. In this research, the final testing result for the model after applying the machine learning algorithm and tsfresh for feature extraction shows good accuracy in RF, DT, SVM, and KNN. and shows no results in some models like LogisticRegression, Naive Bayes, and AdaBoost. Table II shows the final result.

TABLE III. THE FINAL RESULTS

	accuracy	precision	recall	f1-score
RF	99 %	98%	98%	98%
DT	95%	95%	95%	95%
SVM	93%	93%	93%	93%
KNN	82%	83%	82%	82%

We got many results because we tested seven models with balanced and imbalanced data and with over-sampling and under-sampling. Therefore, we will present only the good results we got, which were in over-sampling.

It should be noted that no previous studies used statistical features with the KU-HAR dataset. And the advantage of using statistical features by tsfresh is that it extracts all the statistical automatically.

After training and evaluating the model, tsfresh is applied to extract the feature and machine learning algorithms; we get the result as shown in Table II. The RF gets the best (99%) accuracy, (98 %) precision, (98%) recall, and (98 %) F1-score. Fig. 9. shows the RF confusion matrix for each activity. The DT gets (95%) accuracy, 95% precision, 95% recall, and 95% F1-score Fig. 10. Shows the DT confusion matrix for each activity. The SVM got (93%) accuracy, (93%) precision, (93%) recall, and (93%) F1-score Fig. 11. shows the SVM confusion matrix for each activity. The KNN got 82% accuracy, 83% precision, 82% recall, and 82% F1-score Fig. 12. shows the KNN confusion matrix for each activity.

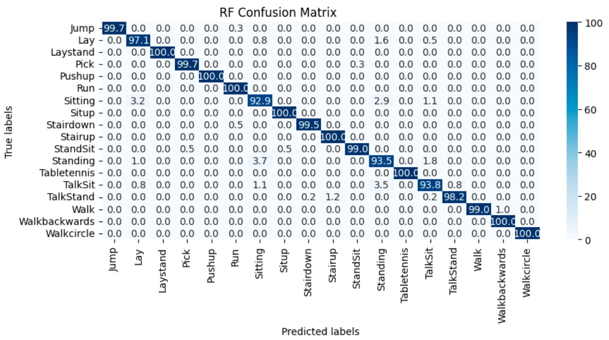

Fig. 9. RF confusion matrix

From the confusion matrix of the RF model in Fig. 9, we realize that all classes get high accuracy, but there is a slight mislabeling. For example, in class Sitting, there is a slight miss with class Lay, and class Standing with class Sitting. The other courses also have mislabeling, but not over 3%, and not for all of them. This miss is small in value and does not affect the model's efficiency.

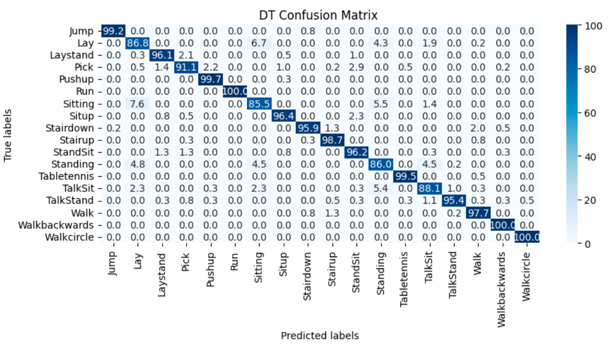

Fig. 10. DT confusion matrix

From the confusion matrix of the DT model in Fig. 10, we realize that all classes get high accuracy, but there is a slight mislabeling in all classes. For example, in class Sitting, there is a slight mislabeling with class Lay and class Lay with class Sitting. The other classes also have mislabeling, but not over 7%, and not for all of them. This miss is small in value and does not affect the model's efficiency.

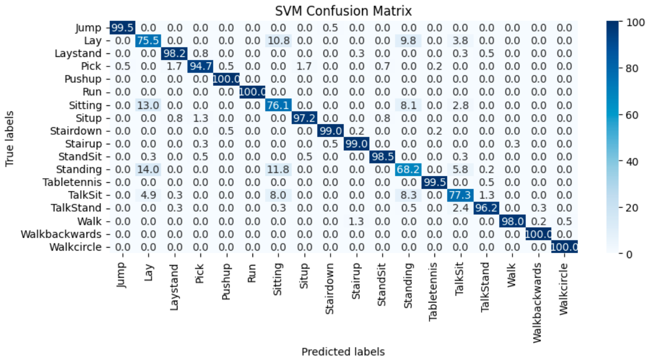

Fig. 11. SVM confusion matrix

From the confusion matrix of the SVM model in Fig. 11, we realize that the miss-labeling value increases to 14%, like in Standing with class Lay. The other courses have also been missed, but not by more than 14%, and only the last two classes show 100% accuracy.

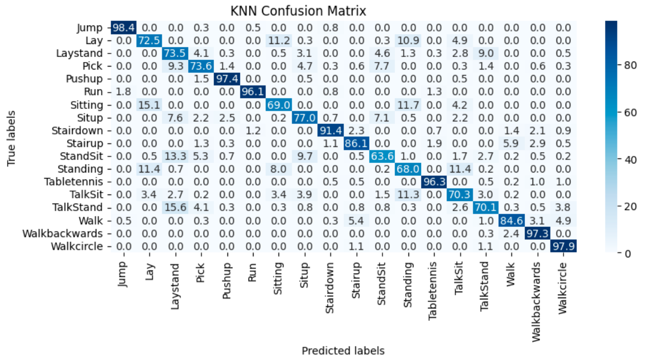

Fig. 12. KNN confusion matrix

From the confusion matrix of the KNN model in Fig. 12, we realize that the missed labeling value increases to 15.6%, like in class TalkStand with class LayStand. The other courses have missed labels, but not over 15.6% and no class shows 100% accuracy. This may be because there is a similarity in features that confuses the model.

V. CONCLUSION

This study highlights the importance of recognizing human activity in several industries, including healthcare, sports, and security, by using the functionalities of smartphone sensors and focusing on extracting statistical features from sensory data collected over time. We aimed to identify 18 fundamental human behaviors gathered using accelerometers and gyroscopes. Our research contribution is to develop an intelligent model using a mobile inertial sensor to recognize human activity. By extracting statistical features from the sensor's raw file, create a new dataset different from the original in size, sample rate, and features. A range of machine learning techniques, including RF, DT, SVM, KNN, LG, NB, and AdaBoost, were employed to assess different levels of accuracy. The KNN model exhibited strong performance in this investigation, with an accuracy rate of 82%. The SVM model was 93% accurate. DT model was 95% correct. The RF model achieves a high accuracy rate of 99 percent. The Logistic Regression, Naïve Bayes, and AdaBoost show an alarming accuracy rate of 10%. This may be because it has a labeling issue or because the number of features is high. This study indicates that extracting statistical features enhances the recognition of activities. Future research should explore novel approaches to fix the problem of mislabeling, which can be applied by feature selection and deep learning algorithms. A hybrid model using a sensor and camera dataset is also recommended.

REFERENCES

[1] L. Schrader *et al.*, "Advanced sensing and human activity recognition in early intervention and rehabilitation of elderly people," *Journal of Population Ageing,* vol. 13, pp. 139-165, 2020.

[2] A. Lentzas and D. Vrakas, "Non-intrusive human activity recognition and abnormal behavior detection on elderly people: A review," *Artificial Intelligence Review,* vol. 53, no. 3, pp. 1975-2021, 2020.

[3] A. Subasi, K. Khateeb, T. Brahimi, and A. Sarirete, "Human activity recognition using machine learning methods in a smart healthcare environment," in *Innovation in health informatics*, pp. 123-144, 2020.

[4] H. Sun and Y. Chen, "Real-time elderly monitoring for senior safety by lightweight human action recognition," in *2022 IEEE 16th International Symposium on Medical Information and Communication Technology (ISMICT)*, pp. 1-6, 2022.

[5] P. P. Ariza-Colpas *et al.*, "Human activity recognition data analysis: History, evolutions, and new trends," *Sensors,* vol. 22, no. 9, p. 3401, 2022.

[6] D. Mukherjee, R. Mondal, P. K. Singh, R. Sarkar, and D. Bhattacharjee, "EnsemConvNet: a deep learning approach for human activity recognition using smartphone sensors for healthcare applications," *Multimedia Tools and Applications,* vol. 79, pp. 31663-31690, 2020.

[7] S. Iloga, A. Bordat, J. Le Kernec, and O. Romain, "Human activity recognition based on acceleration data from smartphones using HMMs," *IEEE Access,* vol. 9, pp. 139336-139351, 2021.

[8] S. E. Ali, A. N. Khan, S. Zia, and M. Mukhtar, "Human activity recognition system using smart phone based accelerometer and machine learning," in *2020 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT)*, pp. 69-74, 2020.

[9] R. Ahmed Bhuiyan, N. Ahmed, M. Amiruzzaman, and M. R. Islam, "A robust feature extraction model for human activity characterization using 3-axis accelerometer and gyroscope data," *Sensors,* vol. 20, no. 23, p. 6990, 2020.

[10] P. Yang, C. Yang, V. Lanfranchi, and F. Ciravegna, "Activity graph based convolutional neural network for human activity recognition using acceleration and gyroscope data," *IEEE Transactions on Industrial Informatics,* vol. 18, no. 10, pp. 6619-6630, 2022.

[11] A. E. Minarno, W. A. Kusuma, H. Wibowo, D. R. Akbi, and N. Jawas, "Single triaxial accelerometer-gyroscope classification for human activity recognition," in *2020 8th international conference on information and communication technology (ICoICT)*, pp. 1-5, 2020.

[12] W. Taylor, S. A. Shah, K. Dashtipour, A. Zahid, Q. H. Abbasi, and M. A. Imran, "An intelligent non-invasive real-time human activity recognition system for next-generation healthcare," *Sensors,* vol. 20, no. 9, p. 2653, 2020.

[13] J. Liu, G. Teng, and F. Hong, "Human activity sensing with wireless signals: A survey," *Sensors,* vol. 20, no. 4, p. 1210, 2020.

[14] H. Shahverdi, M. Nabati, P. Fard Moshiri, R. Asvadi, and S. A. Ghorashi, "Enhancing CSI-based human activity recognition by edge detection techniques," *Information,* vol. 14, no. 7, p. 404, 2023.

[15] G. Bhola and D. K. Vishwakarma, "A review of vision-based indoor HAR: state-of-the-art, challenges, and future prospects," *Multimedia Tools and Applications,* vol. 83, no. 1, pp. 1965-2005, 2024.

[16] E. Ramanujam, T. Perumal, and S. Padmavathi, "Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review," *IEEE Sensors Journal,* vol. 21, no. 12, pp. 13029-13040, 2021.

[17] W. Kong, L. He, and H. Wang, "Exploratory data analysis of human activity recognition based on smart phone," *IEEE Access,* vol. 9, pp. 73355-73364, 2021.

[18] A. Gupta, K. Gupta, K. Gupta, and K. Gupta, "A survey on human activity recognition and classification," in *2020 international conference on communication and signal processing (ICCSP)*, pp. 0915-0919, 2020.

[19] R. K. Athota and D. Sumathi, "Human activity recognition based on hybrid learning algorithm for wearable sensor data," *Measurement: Sensors,* vol. 24, p. 100512, 2022.

[20] F. Demrozi, G. Pravadelli, A. Bihorac, and P. Rashidi, "Human activity recognition using inertial, physiological and environmental sensors: A comprehensive survey," *IEEE access,* vol. 8, pp. 210816-210836, 2020.

[21] M. S. H. Bhuiyan, N. S. Patwary, P. K. Saha, and M. T. Hossain, "Sensor-based human activity recognition: A comparative study of machine learning techniques," in *2020 2nd International Conference on Advanced Information and Communication Technology (ICAICT)*, pp. 286-290, 2020.

[22] D. Thakur, S. Biswas, E. S. Ho, and S. Chattopadhyay, "Convae-lstm: Convolutional autoencoder long short-term memory network for smartphone-based human activity recognition," *IEEE Access,* vol. 10, pp. 4137-4156, 2022.

[23] B. Fu, N. Damer, F. Kirchbuchner, and A. Kuijper, "Sensing technology for human activity recognition: A comprehensive survey," *Ieee Access,* vol. 8, pp. 83791-83820, 2020.

[24] D. R. Beddiar, B. Nini, M. Sabokrou, and A. Hadid, "Vision-based human activity recognition: a survey," *Multimedia Tools and Applications,* vol. 79, no. 41, pp. 30509-30555, 2020.

[25] D. Bouchabou, S. M. Nguyen, C. Lohr, B. LeDuc, and I. Kanellos, "A survey of human activity recognition in smart homes based on IoT sensors algorithms: Taxonomies, challenges, and opportunities with deep learning," *Sensors,* vol. 21, no. 18, p. 6037, 2021.

[26] J. Zhang, Y. Liu, and H. Yuan, "Attention-Based Residual BiLSTM Networks for Human Activity Recognition," *IEEE Access*, vol. 11, pp. 94173-94187, 2023.

[27] S. Raziani and M. Azimbagirad, "Deep CNN hyperparameter optimization algorithms for sensor-based human activity recognition," *Neuroscience Informatics,* vol. 2, no. 3, p. 100078, 2022.

[28] S. M. Bokhari, S. Sohaib, A. R. Khan, and M. Shafi, "DGRU based human activity recognition using channel state information," *Measurement,* vol. 167, p. 108245, 2021.

[29] Z. Sun, Q. Ke, H. Rahmani, M. Bennamoun, G. Wang, and J. Liu, "Human action recognition from various data modalities: A review," *IEEE transactions on pattern analysis and machine intelligence,* vol. 45, no. 3, pp. 3200-3225, 2022.

[30] N. Jaouedi, N. Boujnah, and M. S. Bouhlel, "A new hybrid deep learning model for human action recognition," *Journal of King Saud University-Computer and Information Sciences,* vol. 32, no. 4, pp. 447-453, 2020.

[31] S. Qiu *et al.*, "Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges," *Information Fusion,* vol. 80, pp. 241-265, 2022.

[32] Y. Kong and Y. Fu, "Human action recognition and prediction: A survey," *International Journal of Computer Vision,* vol. 130, no. 5, pp. 1366-1401, 2022.

[33] A. Manaf and S. Singh, "Computer vision-based survey on human activity recognition system, challenges and applications," in *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, pp. 110-114, 2021.

[34] H. Liu, Y. Hartmann, and T. Schultz, "Motion Units: Generalized sequence modeling of human activities for sensor-based activity recognition," in *2021 29th European signal processing conference (EUSIPCO)*, pp. 1506-1510, 2021.

[35] Z. Hussain, Q. Z. Sheng, and W. E. Zhang, "A review and categorization of techniques on device-free human activity

recognition," *Journal of Network and Computer Applications,* vol. 167, p. 102738, 2020.

[36] S. Wan, L. Qi, X. Xu, C. Tong, and Z. Gu, "Deep learning models for real-time human activity recognition with smartphones," *Mobile Networks and Applications,* vol. 25, no. 2, pp. 743-755, 2020.

[37] A. Ray, M. H. Kolekar, R. Balasubramanian, and A. Hafiane, "Transfer learning enhanced vision-based human activity recognition: a decade-long analysis," *International Journal of Information Management Data Insights,* vol. 3, no. 1, p. 100142, 2023.

[38] L. M. Dang, K. Min, H. Wang, M. J. Piran, C. H. Lee, and H. Moon, "Sensor-based and vision-based human activity recognition: A comprehensive survey," *Pattern Recognition,* vol. 108, p. 107561, 2020.

[39] R. G. Ramos, J. D. Domingo, E. Zalama, and J. Gómez-García-Bermejo, "Daily human activity recognition using non-intrusive sensors," *Sensors,* vol. 21, no. 16, p. 5270, 2021.

[40] M. Ehatisham-Ul-Haq, M. A. Azam, Y. Amin, and U. Naeem, "C2FHAR: Coarse-to-fine human activity recognition with behavioral context modeling using smart inertial sensors," *IEEE Access,* vol. 8, pp. 7731-7747, 2020.

[41] J. Wang, T. Zhu, J. Gan, L. L. Chen, H. Ning, and Y. Wan, "Sensor data augmentation by resampling in contrastive learning for human activity recognition," *IEEE Sensors Journal,* vol. 22, no. 23, pp. 22994-23008, 2022.

[42] K. Xia, J. Huang, and H. Wang, "LSTM-CNN architecture for human activity recognition," *IEEE Access,* vol. 8, pp. 56855-56866, 2020.

[43] I. Jegham, A. B. Khalifa, I. Alouani, and M. A. Mahjoub, "Vision-based human action recognition: An overview and real world challenges," *Forensic Science International: Digital Investigation,* vol. 32, p. 200901, 2020.

[44] A. Shenoy and N. Thillaiarasu, "A survey on different computer vision based human activity recognition for surveillance applications," in *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 1372-1376, 2022.

[45] J. Arunnehru *et al.*, "Machine vision-based human action recognition using spatio-temporal motion features (STMF) with difference intensity distance group pattern (DIDGP)," *Electronics,* vol. 11, no. 15, p. 2363, 2022.

[46] Z. Yang, M. Qu, Y. Pan, and R. Huan, "Comparing Cross-Subject Performance on Human Activities Recognition Using Learning Models," *IEEE Access,* vol. 10, pp. 95179-95196, 2022.

[47] S. Bian, M. Liu, B. Zhou, and P. Lukowicz, "The state-of-the-art sensing techniques in human activity recognition: A survey," *Sensors,* vol. 22, no. 12, p. 4596, 2022.

[48] G. Diraco, G. Rescio, P. Siciliano, and A. Leone, "Review on human action recognition in smart living: Sensing technology, multimodality, real-time processing, interoperability, and resource-constrained processing," *Sensors,* vol. 23, no. 11, p. 5281, 2023.

[49] M. Webber and R. F. Rojas, "Human activity recognition with accelerometer and gyroscope: A data fusion approach," *IEEE Sensors Journal,* vol. 21, no. 15, pp. 16979-16989, 2021.

[50] Y. Feng, D. Duives, W. Daamen, and S. Hoogendoorn, "Data collection methods for studying pedestrian behaviour: A systematic review," *Building and Environment,* vol. 187, p. 107329, 2021.

[51] D. Vitazkova *et al.*, "Advances in Respiratory Monitoring: A Comprehensive Review of Wearable and Remote Technologies," *Biosensors,* vol. 14, no. 2, p. 90, 2024.

[52] A. Yazici *et al.*, "A smart e-health framework for monitoring the health of the elderly and disabled," *Internet of Things,* vol. 24, p. 100971, 2023.

[53] A. Hoelzemann, J. L. Romero, M. Bock, K. V. Laerhoven, and Q. Lv, "Hang-time HAR: A benchmark dataset for basketball activity recognition using wrist-worn inertial sensors," *Sensors,* vol. 23, no. 13, p. 5879, 2023.

[54] R. Mondal, D. Mukherjee, P. K. Singh, V. Bhateja, and R. Sarkar, "A new framework for smartphone sensor-based human activity recognition using graph neural network," *IEEE Sensors Journal,* vol. 21, no. 10, pp. 11461-11468, 2020.

[55] N. Sikder and A.-A. Nahid, "KU-HAR: An open dataset for heterogeneous human activity recognition," *Pattern Recognition Letters,* vol. 146, pp. 46-54, 2021.

[56] S. Caro-Alvaro, E. Garcia-Lopez, A. Brun-Guajardo, A. Garcia-Cabot, and A. Mavri, "Gesture-Based Interactions: Integrating Accelerometer and Gyroscope Sensors in the Use of Mobile Apps," *Sensors,* vol. 24, no. 3, p. 1004, 2024.

[57] T. Hasegawa, "Smartphone sensor-based human activity recognition robust to different sampling rates," *IEEE Sensors Journal,* vol. 21, no. 5, pp. 6930-6941, 2020.

[58] R. T. Al_Hassani and D. C. Atilla, "Human activity detection using smart wearable sensing devices with feed forward neural networks and PSO," *Applied Sciences,* vol. 13, no. 6, p. 3716, 2023.

[59] S. K. Yadav, K. Tiwari, H. M. Pandey, and S. A. Akbar, "A review of multimodal human activity recognition with special emphasis on classification, applications, challenges and future directions," *Knowledge-Based Systems,* vol. 223, p. 106970, 2021.

[60] G. Saleem, U. I. Bajwa, and R. H. Raza, "Toward human activity recognition: a survey," *Neural Computing and Applications,* vol. 35, no. 5, pp. 4145-4182, 2023.

[61] K. Muralidharan, A. Ramesh, G. Rithvik, S. Prem, A. Reghunaath, and M. Gopinath, "1D Convolution approach to human activity recognition using sensor data and comparison with machine learning algorithms," *International Journal of Cognitive Computing in Engineering,* vol. 2, pp. 130-143, 2021.

[62] Z. Chen, C. Jiang, S. Xiang, J. Ding, M. Wu, and X. Li, "Smartphone sensor-based human activity recognition using feature fusion and maximum full a posteriori," *IEEE Transactions on Instrumentation and Measurement,* vol. 69, no. 7, pp. 3992-4001, 2019.

[63] V. Ghate, "Hybrid deep learning approaches for smartphone sensor-based human activity recognition," *Multimedia Tools and Applications,* vol. 80, no. 28, pp. 35585-35604, 2021.

[64] R. Mutegeki and D. S. Han, "A CNN-LSTM approach to human activity recognition," in *2020 international conference on artificial intelligence in information and communication (ICAIIC)*, pp. 362-366, 2020.

[65] J. A. Gamble and J. Huang, "Convolutional neural network for human activity recognition and identification," in *2020 IEEE International Systems Conference (SysCon)*, pp. 1-7, 2020.

[66] M. Christ, N. Braun, J. Neuffer, and A. W. Kempa-Liehr, "Time series feature extraction on basis of scalable hypothesis tests (tsfresh–a python package)," *Neurocomputing,* vol. 307, pp. 72-77, 2018.

[67] F. Thabtah, S. Hammoud, F. Kamalov, and A. Gonsalves, "Data imbalance in classification: Experimental evaluation," *Information Sciences,* vol. 513, pp. 429-441, 2020.

[68] E. Rendon, R. Alejo, C. Castorena, F. J. Isidro-Ortega, and E. E. Granda-Gutierrez, "Data sampling methods to deal with the big data multi-class imbalance problem," *Applied Sciences,* vol. 10, no. 4, p. 1276, 2020.

[69] M. Heydarian, T. E. Doyle, and R. Samavi, "MLCM: Multi-label confusion matrix," *IEEE Access,* vol. 10, pp. 19083-19095, 2022.

[70] A. E. Maxwell, T. A. Warner, and L. A. Guillén, "Accuracy assessment in convolutional neural network-based deep learning remote sensing studies—Part 1: Literature review," *Remote Sensing,* vol. 13, no. 13, p. 2450, 2021.

[71] S. Szabó, I. J. Holb, V. É. Abriha-Molnár, G. Szatmári, S. K. Singh, and D. Abriha, "Classification assessment tool: a program to measure the uncertainty of classification models in terms of class-level metrics," *Applied Soft Computing,* vol. 155, p. 111468, 2024.

[72] X. Wang *et al.*, "Evaluating the effectiveness of machine learning and deep learning models combined time-series satellite data for multiple crop types classification over a large-scale region," *Remote Sensing,* vol. 14, no. 10, p. 2341, 2022.

[73] D. Chicco and G. Jurman, "The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation," *BMC genomics,* vol. 21, pp. 1-13, 2020.

[74] M. M. Islam, M. R. Haque, H. Iqbal, M. M. Hasan, M. Hasan, and M. N. Kabir, "Breast cancer prediction: a comparative study using machine learning techniques," *SN Computer Science,* vol. 1, pp. 1-14, 2020.

[75] M. Rottmann, K. Maag, R. Chan, F. Hüger, P. Schlicht, and H. Gottschalk, "Detection of false positive and false negative samples in semantic segmentation," in *2020 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, pp. 1351-1356, 2020.

[76] J. Mijalkovic and A. Spognardi, "Reducing the false negative rate in deep learning based network intrusion detection systems," *Algorithms,* vol. 15, no. 8, p. 258, 2022.

[77] A. M. Carrington *et al.*, "Deep ROC analysis and AUC as balanced average accuracy, for improved classifier selection, audit and explanation," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 45, no. 1, pp. 329-341, 2022.

[78] A. Anwyl-Irvine, E. S. Dalmaijer, N. Hodges, and J. K. Evershed, "Realistic precision and accuracy of online experiment platforms, web browsers, and devices," *Behavior research methods,* vol. 53, no. 4, pp. 1407-1425, 2021.

[79] D. Chicco, N. Tötsch, and G. Jurman, "The Matthews correlation coefficient (MCC) is more reliable than balanced accuracy, bookmaker informedness, and markedness in two-class confusion matrix evaluation," *BioData mining,* vol. 14, pp. 1-22, 2021.

[80] M. A. R. Refat, M. Al Amin, C. Kaushal, M. N. Yeasmin, and M. K. Islam, "A comparative analysis of early stage diabetes prediction using machine learning and deep learning approach," in *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*, pp. 654-659, 2021.

[81] Google. "Google Colab", 2024, https://research.google.com/colaboratory/faq.html#whats-colaboratory (accessed 2024).