Personalized Human Activity Recognition Using Smartphone Technology

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***Abstract*—The project aims to create a system for human activity recognition using data from smartphone sensors. We have to develop a more efficient system using machine learning algorithms for more accurate activity classification and to optimize the system. HAR has several applications in fitness tracking and sports performance analysis used on smartphones. The six daily actions are walking, walking up and down stairs, sitting, standing, and laying. The application's main goal is to identify users' movements using built-in sensors, such as those that monitor acceleration. We will make practical feature selection for the univariate filter method and feature extraction with linear discriminant analysis (LDA). We evaluate multiple models, including the Desicion tree, Random Forest, and Support Vector Classifier, using confusion metrics like accuracy, recall, f1score, and precision. The combination of feature selection and extraction exchanges model performances. Also, performance is measured based on the comparison of overall accuracy for rate of classification between ensemble models. Overall, a decision tree outperformed a voting classifier based on a random ensemble model.**

***Index Terms*—Human activity recognition, smartphone sensors, Desicion Tree,Random Forest,Support Vector Classifier, feature extraction.**

I. Introduction

Human Activity Recognition optimize the time of the work sensor data to autonomously recognize and categorize human movements. Its applications span across diverse fields, including healthcare for personalized monitoring, fitness tracking for goal-setting, assistive products and their related systems for enhancing accessibility, smart environments for automated adjustments, security systems for threat detection, and industrial optimization for how fast people can execute the workflow. By explaining human activities, HAR enables a goal of organization, safety, and how the user is using it across various domains. This project aims workout an efficient Human Activity Recognition (HAR) system using machine learning models to find accurate classification models of human activities based on data from smartphone sensors. The goal is to categorize accurate information using six labeled activities and attributes retrieved from sensor data. Human Activity Recognition (HAR) analyzes human gait using wearable sensors for applications such as smart home monitoring and medical care. Smartphones that include sensors and computational capabilities are better suited for HAR systems. Some ensemble learning techniques use machine learning algorithms including Naive Bayes trees, decision trees, neural networks, k-nearest neighbors, and support vector classifiers to enhance accuracy. We present an ensemble classifier architecture for human activity recognition (HAR) that uses wireless network technology and compares the performance of single classifiers to the Adaboost ensemble learning method in a variety of scenarios. Wearable smart devices are generally utilized for human activity recognition in healthcare by applying deep learning to balance accuracy and cost.

Wearable smart devices [4] are increasingly used for human activity recognition, particularly in healthcare. A novel approach machine learning models, like decision trees and random forests have limitations. A new available method using wearable devices uses the Extreme Gradient Boosting algorithm to preprocessing the data and recognize human activities .

II. Literature Review

Alanazi et al. [1] introduced an XGBoost method alongside dimensionality reduction using PCA for Human Activity Recognition (HAR). Comparing it with previous machine learning or deep learning approaches, their method achieves a balance between recognition accuracy and model complexity, making it suitable for resource-constrained scenarios. Among these methods, the LightGBM algorithm demonstrated the highest accuracy.

R.Ge et al. [2] cat boost and other algorithms, like the gradient boosting algorithm, for efficient handling of categorical features. A cat boost provides greater accuracy.

Lin et al. [3] used ensemble learning methods: bagging based on Random Forest had the highest accuracy, and based on KNN had the lowest accuracy.

Tee et al. [4] High accuracy rates in predicting activities, with specific activities like going from bed to toilet and working achieving accuracy scores of 0.99 and 0.9985 respectively.

Yulita et al. [5] used linear discriminant analysis (LDA) to emphasize the importance of high sampling rates for data acquisition in HAR, commonly using 50 Hz for inertial data.The work emphasizes the necessity of high sample rates and preprocessing in HAR data gathering, with AdaBoost SVM attaining 0.96 accuracy. at C = 0.70, indicating potential for other human activity recognition.

Sri Harsha et al. [6] High accuracy rates were achieved for activity recognition. The study reveals seven machine learning algorithms with 0.99 accuracy rates for human activity recognition, emphasizing the importance of optimized feature selection and the potential of smartphones for this task.

Webber et al. [7] Comparison of machine learning models for activity recognition. The Kalman filter is the most efficient fusion method for HAR systems, outperforming baseline data in accuracy and processing time, despite the need for computational power.

Sidibe et al. [8] used ensemble methods. Machine learning models showed efficient classification models of human activities. The Naive Bayes algorithm showed high accuracy for activities like walking, laying, and standing. The results showed that the suggested system was tested for seven distinct physical activities and achieved an overall accuracy of 0.99 using Adaboost and random forest.
Das et al. [9] The suggested SC and MSSC methods show better performance compared to voting methods. The evaluation of the UT interaction and DARPA Y1 datasets demonstrates promising results. DARPA Y2Gapfilling dataset poses more challenges due to missing action units.

III. Methodology

The present study applied the model to the widely used UCI HAR dataset alongside a special focus on ensemble techniques to boost the accuracy of the HAR project.The output of different models is compared to find the optimal model with the highest accuracy.

A. Dataset Description

The Dataset is primarily used for activity recognition tasks, where the aim is to classify the activities according to the sensor information. There are 10,299 tuples and 561 features in total. The sensor data was gathered from smart phones donned by people carrying out six different activities.

TABLE I: Dataset Attributes

Dataset name	**HAR (UCI HAR)**
No. of instances	10299
No. of features	561
Target Variable	Activity
No. of classes	6
Data split	70% training, 30% testing
Shape of training data	(7352,563)
Shape of testing data	(2947,563)
Activities	Static(Sitting,Standing,Laying), Dynamic(Walking)
Subjects	30
Feature Types	Numerical, Categorical
Sensor Used	Accelerometer , Gyroscope

TABLE I describes about the dataset and the dataset attributes.

TABLE II: Class Distribution

Activity	**Number of Instances**
Walking	1722
Walking upstairs	1544
Walking Downstairs	1406
Sitting	1777
Standing	1906
Laying	1944

TABLE II To ensure the uniformity in the dataset the distribution of instances across different activities are nearly close to each other.Below table shows the distribibution across various classes.

B. Preprocessing

The first stage is preprocessing of data which is done to improve the quality and efficiency of learning by transforming unprocessed data into a suitable format for modeling. This involves checking the dataset for missing values, performing feature engineering, and applying standard scaling to ensure equal contribution to the learning process. Dimensionality reduction is applied to decrease computational complexity and prevent overfitting in human activity recognition datasets. PCA standardizes features, computes the covariance matrix, and determines eigen vectors and values. The eigenvectors with greater corresponding eigenvalues are considered principle components.

C. Model Architecture

The proposed model shows the comparision of individual machine learning models with that of ensemble models.This study tested on various individual models such as Decision Tree , Support vector classefier , Random forest , K Nearest Neighbours.

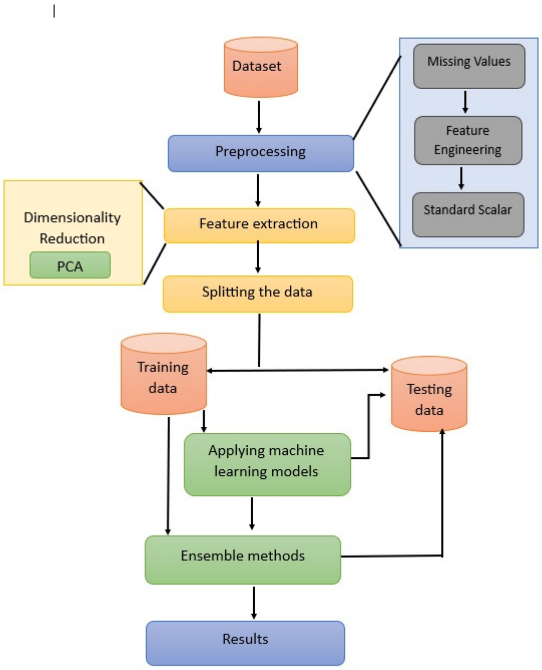

Fig. 1: Flow Diagram

D. Machine Learning Models

Human Activity Recognition (HAR) seeks to automatically identify and categorize human actions using sensor data. The ultimate objective is to build algorithms and systems with high reliability and accuracy that can identify actions like running, walking, sitting, standing,and more.Machine learning models are crucial for training and validating data to achieve this goal. [8].

*1) **Decision Tree Classifier**:* The decision tree classifier, an adaptive machine learning method produce subsets of data having as pure class labels as possible through continuously partitioning the data in accordance to input Feature values.The procedure continues until a predetermined end point is achieved, such as a maximum depth or a minimum number of samples per leaf. Decision Trees provide interpretability in human activity recognition, which simplifies understanding of the decision-making process. They are suitable for complicated data sets as they are capable of handling non-linear relationships between features and target variables.

$$T(X) = \sum_{i=1}^{N} y_i \cdot \nVdash_{R_i}(X) \tag{1}$$

T(X): The output value of the function T when the input is X. This is the result of certain computations.
N: Total number of terms added together.

*2) **K Nearest Neighbours**:* A simple and clear supervised machine learning method to tackle regression and classification the task is K-Nearest Neighbors (KNN). It relies on belief that similar data points are likely to be part of the same class. Because KNN leverages feature vectors to determine similarities between various activities, It may be beneficial in the context of human activity recognition (HAR). Because it doesn't make any assumptions about the data's underlying distribution, it can be utilized for assessing non linear relationships between features and activities. However, it can turn computationally expensive during inference, and its accuracy may deteriorate with high-dimensional data.

$$\hat{y}(\mathbf{x}) = \text{mode}\{y_i : \mathbf{x}_i \in \text{kNN}(\mathbf{x})\} \tag{2}$$

y i: These are the target values (or labels) associated with the training data points.
The training dataset's feature vectors (input data points) are denoted by and , respectively.

*3) **Support Vector Classifier**:* SVC is referred to as support vector classifier is another machine learning model that handles high dimensional data . It aims to find the hyperplane that best divides the classes in feature space. This project used SVC as it is robust to noise and unseen data hence fits best for real worls tasks.

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i \langle \mathbf{x}_i, \mathbf{x} \rangle + b\right) \tag{3}$$

f(x) is the output of a classifier function for a given input vector. alpha i The coefficients for each training data point (x, y) are listed below.

*4) **Random Forest Classifier**:* The Random Forest Classifier, or RFC for short, is an ensemble learning method that constructs several decision trees during training and returns the average prediction (regression) of the individual trees or the mode of the classes. Random Forests are extremely useful in Human Activity Recognition (HAR) since they may handle complex relationships and non-linear associations between features and activities. Random Forests, which combine several decision trees to produce robust predictions, are ideal for HAR tasks that may entail complicated trends and interactions between multiple sensors.

$$\hat{y}(x) = \text{mode}\{\text{trees}(x)\} \tag{4}$$

modetrees(x): This section calculates the mode of decision tree predictions for input .

*5) **Voting**:* Voting: Voting is a simplistic but fast ensemble method of learning which combines results from multiple base models to create the most accurate prediction. In voting, a weighted value calculated from the individual assumptions calculated by each base model for a given input is used for selecting the final prediction.

$$\hat{y} = \text{mode}\{y_i : i = 1, 2, ..., N\} \tag{5}$$

y is This represents the predicted value. y cap It's the value that we estimate or predict for a given scenario.

Algorithm 1 Ensemble Techniques

1: Loaded the data containing smartphone sensor data.
2: Data preprocessing is applied by handling missing values and standardizing features.
3: Dimensionality reduction is applied to reduce the number of dimensions and only extract important features.
4: A few models are chosen depending on the peculiarities of our dataset and the project's objectives.
5: The models selected are:

$$\text{Model} = \begin{cases} \text{Decision Tree Classifier} & \text{if model}_1 \\ \text{SVC (Support Vector Classifier)} & \text{if model}_2 \\ \text{Random Forest Classifier} & \text{if model}_3 \\ \text{Logistic Regression} & \text{if model}_4 \\ \text{K Nearest Neighbors} & \text{if model}_5 \end{cases}$$

The model $_i$ conditions are determined by the dataset's properties and project aims.

6: The dataset is separated into training and testing data.
7: Models are applied to training data and assessed using a variety of metrics, including accuracy, precision, recall, and F1 score.
8: We also used ensemble techniques wherein multiple individual models are combined using Voting Classifier or Stacking Classifier to combine predictions help enhance the overall performance of the model.
9: The model is trained with various combinations of ensemble models and studied for finding the best model.

IV. Results

A. Performance Metrics

Performance metrics, in general, refer to the Quantitative metrics are used to assess the efficiency, effectiveness, and success of a given process, system, or activity. These metrics can vary widely depending on the context, but they typically involve assessing key indicators such as productivity, quality, timeliness, cost-effectiveness, customer satisfaction, and overall performance goals.

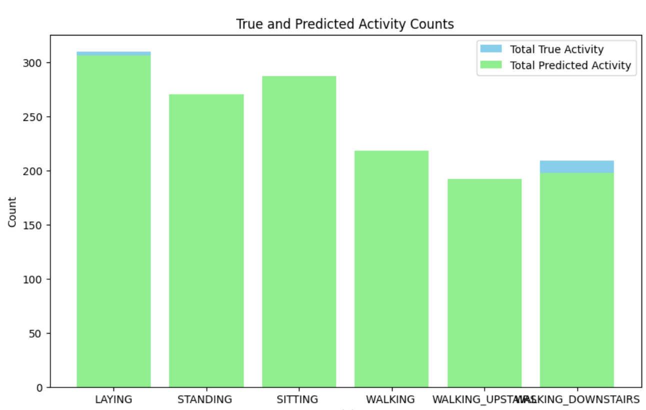

Fig. 2: Desiciontree,RandomForest

Figure 2 illustrates the bar graph of Desicion Tree,Random forest

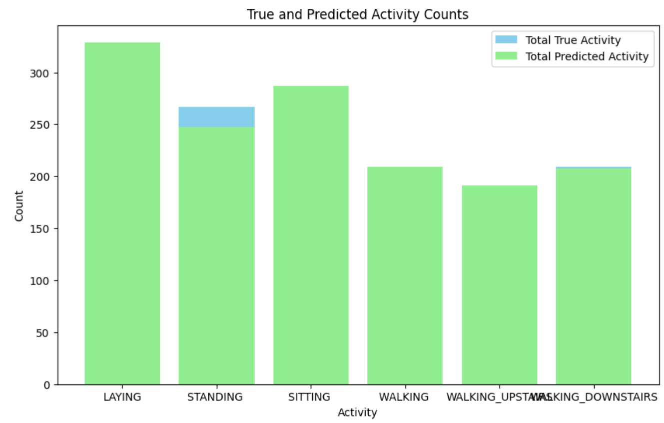

Fig. 3: Randomforest,svm

Figure 3 illustrates the bar graph of Random forest,SVM

TABLE III: Model Performance

S.no	Model	Accuracy
1	Desicion Tree	0.95
2	Random Forest	0.94
3	KNN	0.93
4	SVC	0.39
5	Rondom Forest ,Desicion Tree	0.95
6	Rondom Forest,SVC	0.96
7	SVC,KNN,Desicion Tree	0.66
8	Rondom Forest,SVC,Desicion Tree	0.98

The table III displays accuracy scores for different classification models: Decision Tree (0.94), Random Forest (0.95), KNN (0.93), SVC (0.39), combinations like Random Forest with Decision Tree (0.95), Random Forest with SVC (0.96), SVC with KNN and Decision Tree (0.66), and Random Forest with SVC and Decision Tree achieving the highest accuracy at 0.98.

B. Performance Evaluation

The ROC curve is an important tool for evaluating binary classifier performance, as it reveals the model's accuracy and intelligent classification selections, identifies strengths and flaws, and guides future predictive modeling. The ROC curve offers a more nuanced perspective on a binary classifier's performance by considering .Both the true positive rate (TPR) and the false positive rate (FPR) were calculated at various categorization levels.

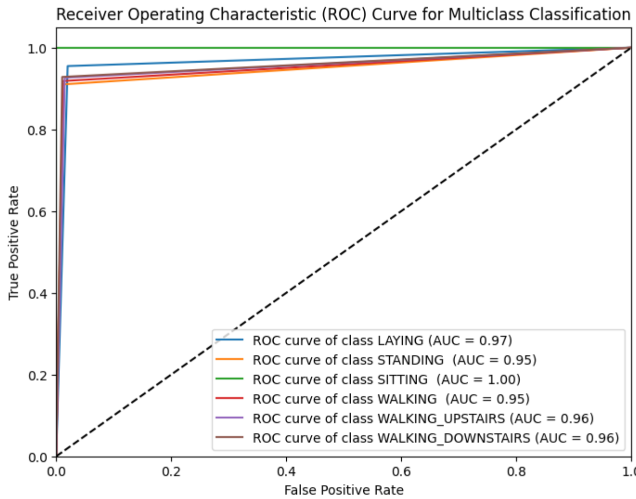

Fig. 4: Desicion Tree ROC Curve

Figure 4 illustrates the ROC Curve of Desicion Tree, showcasing an expansive area under the curve of 0.94 and a true positive rate.

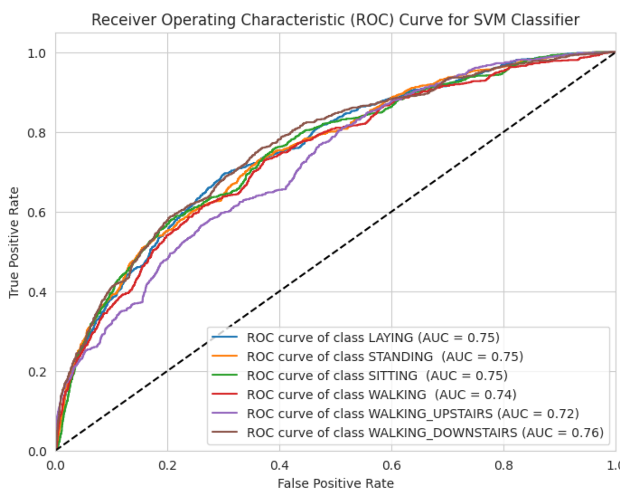

Fig. 5: SVC ROC Curve

Figure 5 illustrates the ROC Curve of SVC, showcasing an expansive area under the curve of 0.39 and a true positive rate.

C. Confusion matrix

A confusion matrix is a tabular depiction of a classification model's performance, including accuracy, precision, recall, and F1-score across classes.

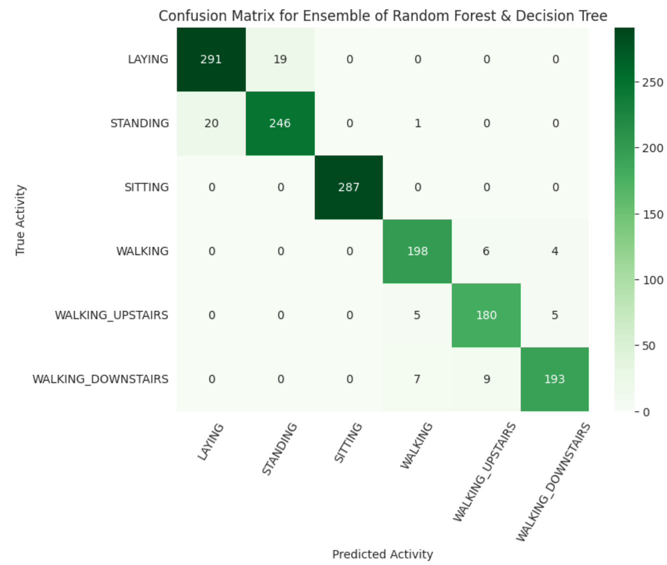

Fig. 6: Confusion matrix for Random forest and Decision Tree

The confusion matrix in Figure 6 shows the Desicion Tree,Random Forest classifier performs well on this task, particularly for classes 200 and 280. This indicates the chosen features are effective for classifying activities using this model.

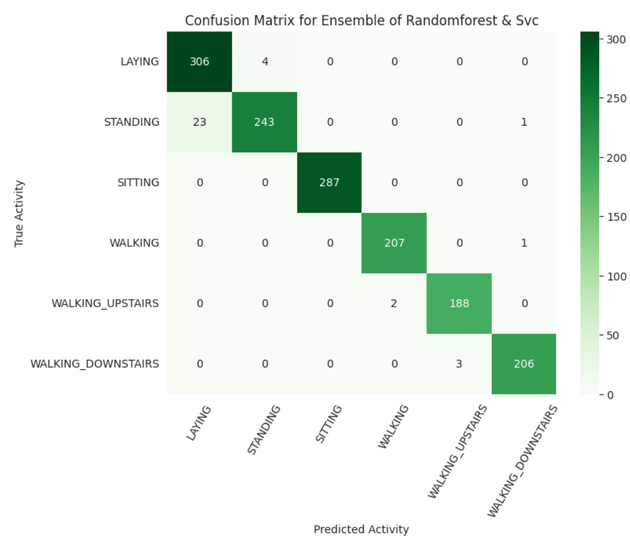

Fig. 7: Confusion matrix for Random forest and SVC

The confusion matrix in Figure 7 shows the RaandomForest,Supportvectorclassifier performs well on this task, particularly for classes 200 and 320. This indicates the chosen features are effective for classifying activities using this model.

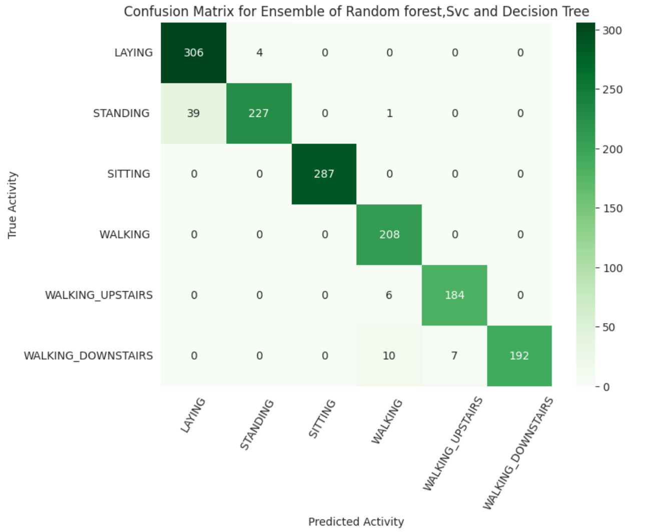

Fig. 8: Confusion matrix for Random forest,SVC and Decision Tree

The confusion matrix in Figure 8 shows the Rondomforest,supportvectorclassifier,desiciontree,classifier performs well on this task, particularly for classes 200 and 306. This indicates the chosen features are effective for classifying activities using this model

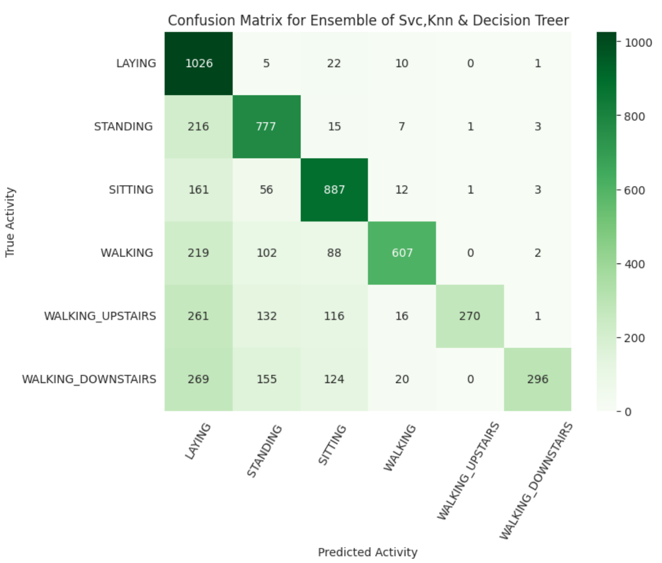

Fig. 9: Confusion matrix for KNN,SVC and Decision Tree

The confusion matrix in Figure 9 shows the Supportvectorclassifier,knn,desiciontree, classifier performs well on this task, particularly for classes 200 and 306 and . This indicates the chosen features are effective for classifying activities using this model

V. Conclusion

Lastly, this article goes through the necessary requirements for a successful HAR (human activity recognition) system using smartphone sensor data. We are likely to achieve accurate results on human activities for some different applications, which comprise fitness tracking, sports performance, and healthcare monitoring, by concatenating machine learning and ensemble methods. Following extensive research and evaluation, we determined that ensemble models, notably the Voting Classifier, The decision tree model outperformed the other classifiers. To improve classification accuracy, we employed practical feature selection and extraction approaches such as univariate filtering and linear discriminant analysis (LDA). We aimed to identify the most successful machine learning models and ensemble strategies through thorough evaluation.

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