# Human Activity Analysis using Machine Learning Classification Techniques

**Zameer Gulzar, A.Anny Leema, I.Malaserene**

*Abstract: In recent times, smart phones are playing a vital role to recognize the human activities and became a well-known field of research. Detail overview of various research papers on human activity recognition are discussed in this paper. Artificial Intelligence(AI) models are developed to recognize the activity of the human from the provided UCI online storehouse. The data chosen is multivariate and we have applied various machine classification techniques Random Forest, kNN, Neural Network, Logistic Regression, Stochastic Gradient Descent and Naïve Bayes to analyse the human activity. Besides building AI models, the dimension of the dataset is reduced through feature selection process.Precision and Recall values were calculated and a Confusion Matrix for each model was made. Experiment results proved that the Neural Network and logistic regression provides better accuracy for human activity recognition compared to other classifiers such as k-nearest neighbor (KNN), SGD , Random Forest and Naïve Bayes though they take higher computational time and memory resources.*

*Keyword: Artificial Intelligence(AI) models are developed to recognize the activity of the human from the provided UCI online storehouse.*

## I. INTRODUCTION

To recognize, detect and classify the activity of the human many applications have been developed with human centered monitoring and researchers have proposed different solutions.Human activity recognition is one of the important technology to monitor the dynamism of a person and this can be attained with the support of Machine learning techniques. Threshold-based algorithm is simpler and faster which is often applied to recognize the human activity. But Machine algorithm provides the reliable result. Numerous sensors have been deployed to observe the human dynamic characteristics. This paper intends to measure the effectiveness of various machine learning classification algorithms.Low cost and commercial smartphones are used as sensors to record the activities of the human. Different studies have been conducted in the intelligent environment to observe the activities of the human. We developed AI Models for "Human Activity Recognition using smartphones Data set" from UCI online storehouse. The motivation behind our work is to implement machine learning algorithms in real world datasets so that their accuracy can be studied and effective conclusions can be drawn.

**Zameer Gulzar\*,** B S AbdurRahman Crescent Institute of Science and Technology
**A.Anny Leema**, Vellore Institute of Technology
**I.Malaserene** ,Vellore Institute of Technology

## II. BACKGROUND

Anguita et al. (2012) demonstrated how activities of human are recognized by exploitingdissimilar sensors so as to give adjustment to exogenous registering assets. At the point when these sensors are joined to the subject's body, they license nonstop checking of various physiological signs. He has presented a framework to recognize human physical activities usinginertial navigation system. As these cell phones are constrained as far as vitality and processing power, equipment benevolent methodology is proposed for multiclass characterization. This strategy adjusts the standard Support Vector Machine (SVM) and endeavors fixed-point number juggling for computational cost decrease. An examination with the customary SVM demonstrates a noteworthy improvement as far as computational expenses while keeping up comparative precision, which can add to grow increasingly maintainable frameworks for AmI.[1]

Shahroudy et al. (2016) examined late methodologies top to bottom based human movement examination accomplished exceptional execution and demonstrated the viability of 3D portrayal for arrangement of activity classes. As of now accessible profundity based and RGB+D-based activity acknowledgment benchmarks have various restrictions, including the absence of preparing tests, unmistakable class names, camera perspectives and assortment of subjects. In this paper presented a vast scale dataset for human activity acknowledgment of 56,000 video tests and 4 million edges, gathered from 40 particular subjects. It contains sixty diverse activity classes including day by day, shared, and wellbeing related activities. Moreover, another repetitive neural system structure is proposed to demonstrate the long haul transient connection of the highlights for all the body parts, and use them for proper activity characterization. Finally demonstrated the benefits of applying profound learning strategies over cutting edge hand that includes cross-subject and cross-assessment criteria for the chosen dataset. [2]

Oyelade et al. (2010) considered the capacity to screen the advancement of understudies' scholarly execution is a basic issue to the scholastic network of higher learning. A framework for breaking down understudy's outcomes dependent on group examination and utilizations standard measurable calculations to mastermind their scores information as indicated by the dimension of their execution is depicted.Inorder to assess the academic performance of the students, cluster analysis and standard statistical algorithms are used to the considered student dataset containing student score of one particular semester.

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The number of clusters to be obtained is given as input for the chosen random samples. The arithmetic mean of each cluster is obtained and the process is repeated until there is no change in the data points. The performance is evaluated using deterministic model for the chosen semester with offered nine courses and applied fuzzy model to predict their academic performance. [3]

Vesantoet al. (1999) contemplated oneself sorting out guide (SOM) is a productive apparatus for representation of multidimensional numerical information. In this paper, a review and order of both old and new strategies for the perception of SOM is displayed. The reason for existing is to give a thought of what sort of data can be gained from various introductions and how the SOM can best be used in exploratory information perception. The majority of the displayed techniques can likewise be connected in the broader instance of first making a vector quantization and afterward a vector projection [4]

Viola et al. (2010) presented an idea for programmed concentrating on highlights inside a volumetric informational index. The client chooses a center, i.e., object of enthusiasm, from a lot of pre-characterized highlights. The framework proposed here naturally decides the most expressive view on this component. A trademark perspective is evaluated by a novel data theoretic system which depends on the shared data measure. Perspectives change easily by changing the concentration starting with one element then onto the next one. This instrument is constrained by changes in the significance dissemination among highlights in the volume. The most astounding significance is allotted to the element in core interest. Aside from perspective determination, the centering component additionally directs visual accentuation by appointing an outwardly increasingly unmistakable portrayal. To permit a reasonable view on highlights that are regularly impeded by different pieces of the volume, the centering for instance consolidates remove sees.[5]

Jiang et al. (2009) considered learning an ideal Bayesian system classifier is a NP- difficult issue, learning-improved innocent Bayes has pulled in much consideration from scientists. In this paper, improved calculations and proposed a covered up innocent Bayes (HNB). In HNB, a shrouded parent is made for each characteristic which joins the impacts from every other property. HNB is tested as far as characterization exactness, utilizing the 36 UCI informational collections chosen by Weka, and contrast it with gullible Bayes (NB), specific Bayesian classifiers (SBC), innocent Bayes tree, tree-expanded guileless Bayes, and found the middle value of one-reliance estimators (AODE). The exploratory outcomes demonstrate that HNB essentially beats NB, SBC, NBTree, TAN, and AODE. In numerous information mining applications, a precise class likelihood estimation and positioning are likewise attractive. [6]

Vincenzi et al. (2011) presented a demonstrating structure that joins AI strategies and Geographic Information Systems to help the administration of an essential aquaculture species, Manila shellfish (Rudi tapes philippinarum). They utilizedVenice tidal pond (Italy), the primary site in Europe for the generation of R. Philippinarum, to represent the capability of this demonstrating approach. To research the relationship between the yieldofR. philippinarum and a lot of ecological variables, utilized a Random Forest (RF) calculation. The RF demonstrate was tuned with an expansive informational index (n = 1698) and approved by an autonomous informational collection (n = 841). By and large, the model gave great expectations of site-explicit yields and the examination of minor impact of indicators demonstrated considerable understanding among the displayed reactions and accessible natural learning for R. philippinarum. [7]

Jie Hu et al. (2013) proposed the method to recognize the human facial expressions from the recorded videos. The input is bounding boxes detected from sequence of images represented in three layers and the chosen Weizmann dataset contains nine human actions of ten different peoples. The model built contain the spatial and temporal part to capture the typical characteristics. Random forest method is applied on the Weizmann, UCF and facial expression datasets to recognize the human behavior and obtained the improved performance on the Weizmann dataset.[8]

Aggarwal et al. (2011).Discussed Space-time volume approaches and sequential approaches to recognize the activities form the input images.[9] The greater part of these applications require a robotized acknowledgment of abnormal state exercises, made out of various straightforward (or nuclear) activities of people. This article gives a point by point diagram of different best in class investigate papers on human action acknowledgment. A methodology based scientific classification is picked that analyzes the points of interest and restrictions of each methodology.Eneaer al.(2016) discussed the usage of Low cost RGB-D sensors in surveillance, human computer interaction and computed features from the skeleton joints. Histogram was developed from the skeleton features which was denoted as various key poses.The current methodologies concentrated on minor AI estimates which don't give the best outcomes when contrasted with the presently accessible arrangements. They are inclined to overfitting, under fitting, on account of choice trees in Random Forest.[10]

Qingzhong et al (2018) proposed a method to identify human activity using smartphone sensor data based on two categories motion based and phone movement based. After extracting features machine learning classification models were implemented to analyse the human activity. Finally performance is analysed using Convolutional Neural Network [11]. Ms.S.Roobini et al (2019) used deep learning approach to identify the human motion. And also compared Convolutional Neural Network with Long-Short Term Memory and Recurrent Neural Network with Long-Short Term Memory, finally proved that Recurrent Neural Network with Long Short Term Memory (RNNLSTM) provides better accuracy with lower mean absolute percentage error. Hence they suggested RNNLSTM can be used to reduce the human loss of lives in recognizing the activities of human in real world[12]. Human activity recognition is an embryonic research field in smart environments.

The performance of the human activities can be identified by extracting the features from the raw data sensors after preprocessing and segmentation steps. Feature selection plays an important role in activity recognition, hence appropriate features has to be chosen, dimensionality reductions has to be applied if necessary before passing it to the classifier.([13], [14], [15]).

### III. IMPLEMENTATION

#### A. DATA COLLECTION

Machine learning is the new big thing in the world of computer science. The motivation behind this project is to implement machine learning algorithms in real-world data sets so that their accuracy can be studied and effective conclusions can bedrawn. In this task, we develop AI models for "Human Activity Recognition Using Smartphones Data Set" from UCI (University of California Irvine) online storehouse. This informational index has been gathered from chronicles of 30 human subjects caught by means of cell phones empowered with installed inertial sensors. Many AI courses utilize this information for educating purposes. This is a multi-arrangement issue. The informational collection has 10,299 lines and 561 segments. There are thirty volunteers of age group 18-50 years and examinations done in that. Every individual performed physical activities like WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a cell phone on the midsection. Utilizing its implanted accelerometer and gyrator, we caught 3-pivotal straight increasing speed and 3-hub rakish speed at a steady rate of 50Hz. The analyses have been video- recorded to name the information physically. The sensor signals (accelerometer and whirligig) were pre-prepared by applying clamor channels and after that tested in fixed- width sliding windows of 2.56 sec.

The sensor quickening signal, which has gravitational and body movement parts, was isolated utilizing a Butterworth low-pass channel into body speeding up and gravity.The gravitational power is accepted to have just low-recurrence parts, subsequently a channel with 0.3 Hz cutoff recurrence was utilized. From every window, a vector of highlights was acquired by computing factors from the time and recurrencearea. The data is a multivariate and Orange Tool has been used for implementing classification algorithms. Also, a Neural Network has also been implemented in Python with drop outs which in turn gave betterresults. The packages TensorFlow, Keras, NumPy are imported in python to perform the planned task.

#### B. DESIGN APPROACH

Since the data is a multivariate classification problem we have used supervised and unsupervised learning algorithms. Orange Tool has been used for implementation and Neural Network is implemented in Python with drop outs which in turn gave betterresults.The dataset was fed into the modules for Random Forest, kNN, Neural Network, Logistic Regression, Stochastic Gradient Descent and Naive Bayes. Their Precision and Recall Values were calculated and a Confusion Matrix for each model was made.The architecture diagram of the proposed system is shown in Fig:1 . Neural Network implementation was done using python as shown in Fig:2.
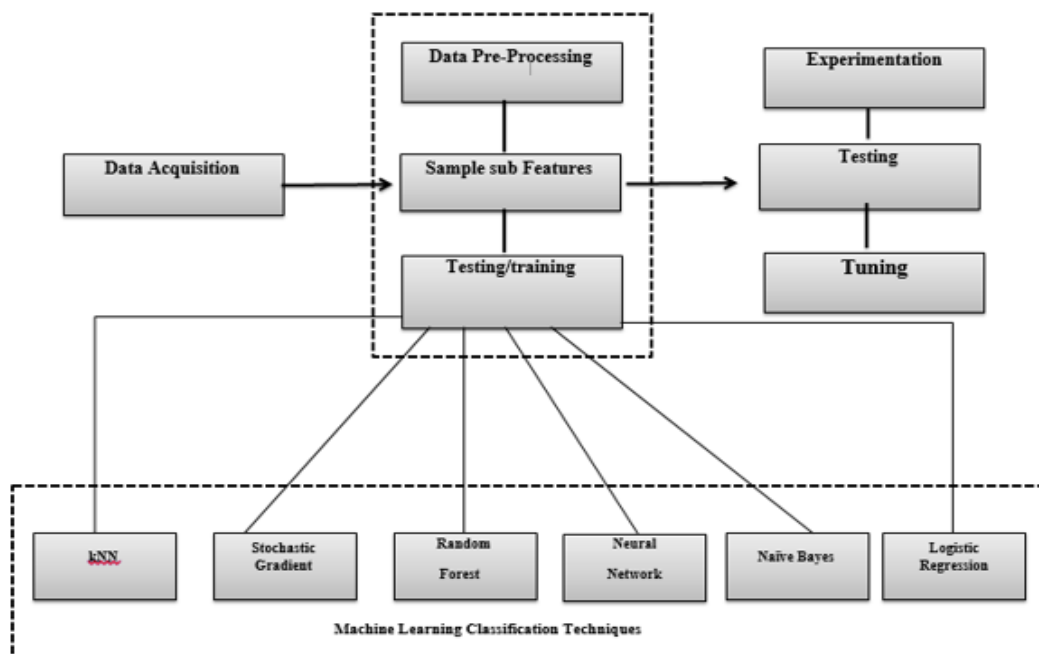


**Fig:1 Architecture diagram of the Proposed System**

Neural Network was implemented using Python where Keras over Tensorflow was used. The basic concept is same as the Neural Network given in Orange, however, this approach differs by providing drop outs in the

model.Irregular timberland is a gathering learning technique utilized for grouping, relapse and different assignments. Arbitrary Forest forms a lot of choice trees.
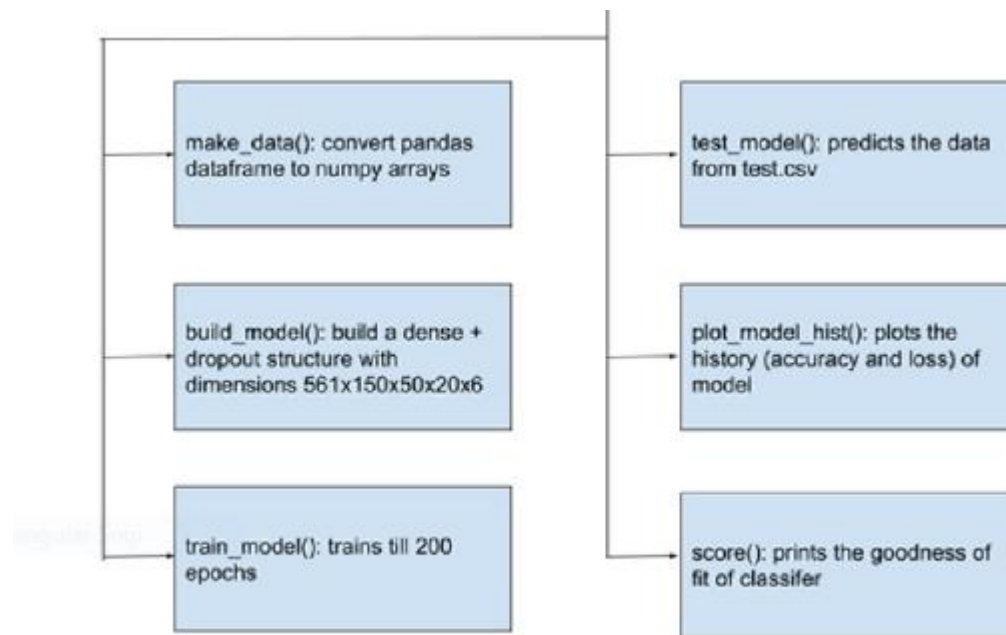


**Fig: 2 Diagram for Neural Network using Python**

Random Forest works for the both classification and or regression tasks. Arbitrary forests forms a lot of choice trees. Each tree is created from a bootstrap test from the preparation information. Determine what number of choice trees will be incorporated into the woodland (Number of trees in the timberland), and what number of characteristics will be self-assertively drawn for thought at every hub. In the event that the last isn't indicated (choice Number of properties… left unchecked), this number is equivalent to the square base of the quantity of traits in the information. Unique Breiman's proposition is to develop the trees with no pre-pruning, however since pre-pruning regularly works great and is quicker, the client can set the profundity to which the trees will be developed.

The kNNis one of the classification methods where no prior knowledge about the data distribution is required. Set the value for k which represents the number of nearest neighbors. The unknown datapoint will be classified as the class from the bunch of the labeled points among its nearest neighbor. Here the distance formula is used and it can be either Manhattan or Euclidean. KNN gadget utilizes the calculation that looks for k nearest preparing models in highlight space and uses their normal as forecast.kNN algorithm gives the accuracy of 96.6% in tracking human activity , when k is 5.

The Stochastic Gradient Descent widget uses stochastic gradient descent that minimizes chosen loss function with linear function. Decide the algorithm parameters for classification loss function, regression loss function and norms to prevent overfitting. Finally fix the learning parameters and result is obtained depends upon the learning

rate. The initial learning rate is 0.0100 with constant and number of iterations is fixed as 1000, number of passes through the training data.

Naive Bayes is a probabilistic model and the predictions from the data in real time is made faster. After loading the dataset, the following functions iscarried out the for the working of themodel:

- make_data(): convert pandas dataframe to numpyarrays
- build_model(): build a dense + dropout structure with dimensions561x150x50x20x6
- train_model(): trains till 200 epochs
- test_model(): predicts the data fromtest.csv
- plot_model_hist(): plots the history (accuracy and loss) ofmodel
- score(): prints the goodness of fit ofclassifier

Logistic regression standard model was incorporated with a loss function and chosen the regularization type as either L1 or L2 and set the cost strength. It gives the good result compared to Naïve Bayes in human activity analysis. It is one of the best performing models and provided improved accuracy compared to other machine learning techniques. It can handle any nonlinear effects and reduce the noise.

### C. RESULTS &DISCUSSION

The following Fig 3 shows the accuracy of all our approaches in the Orange tool.

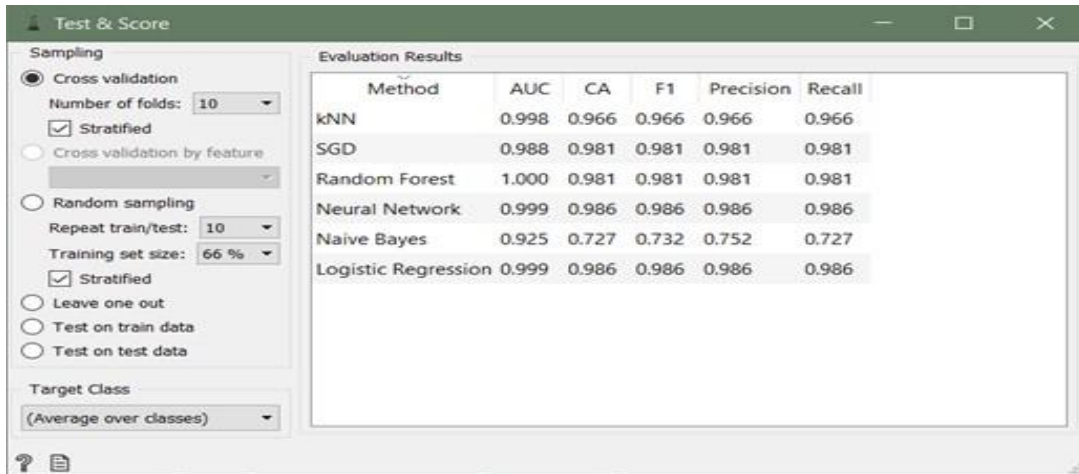| Method | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| kNN | 0.998 | 0.966 | 0.966 | 0.966 | 0.966 |
| SGD | 0.988 | 0.981 | 0.981 | 0.981 | 0.981 |
| Random Forest | 1.000 | 0.981 | 0.981 | 0.981 | 0.981 |
| Neural Network | 0.999 | 0.986 | 0.986 | 0.986 | 0.986 |
| Naive Bayes | 0.925 | 0.727 | 0.732 | 0.752 | 0.727 |
| Logistic Regression | 0.999 | 0.986 | 0.986 | 0.986 | 0.986 |

**Fig: 3Test ad Score**

In this, we can see Naive Bayes has the least precision with 0.752 whereas Logistic Regression and Neural Network gave best precision at 0.986. Fig 4 shows the comparison of precision for difference classifiers and Fig 5 shows the model accuracy. Fig 6 depicts the model loss. Fig 7 shows the snippet of the proposed work and Test Accuracy which clearly indicates neural network gave 99.55% accuracy for the testing data set which is better than the former approach.
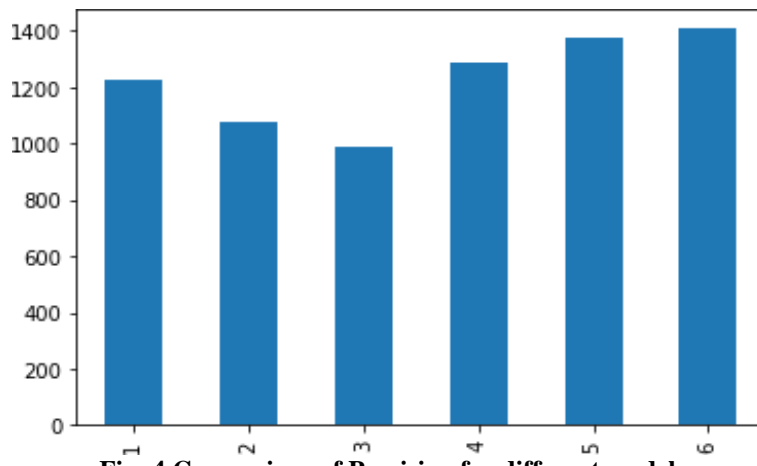
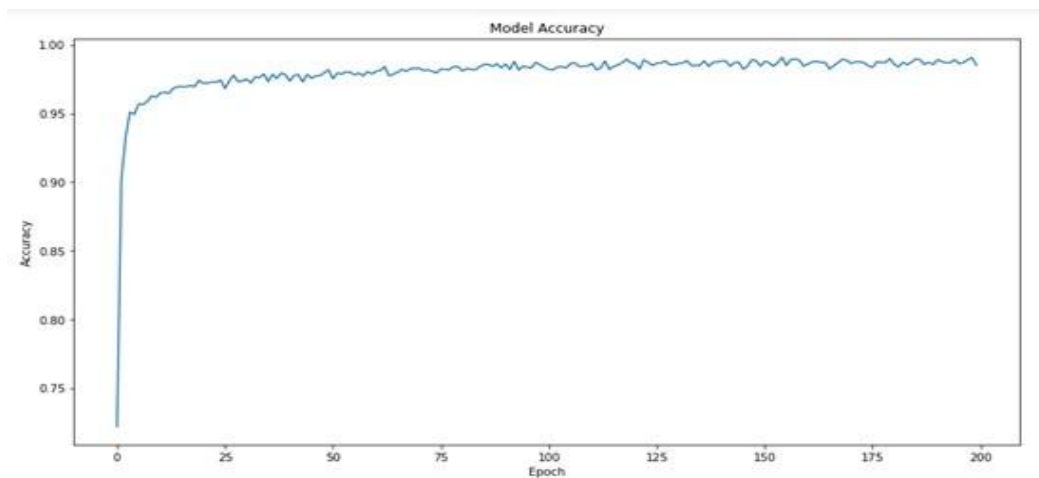

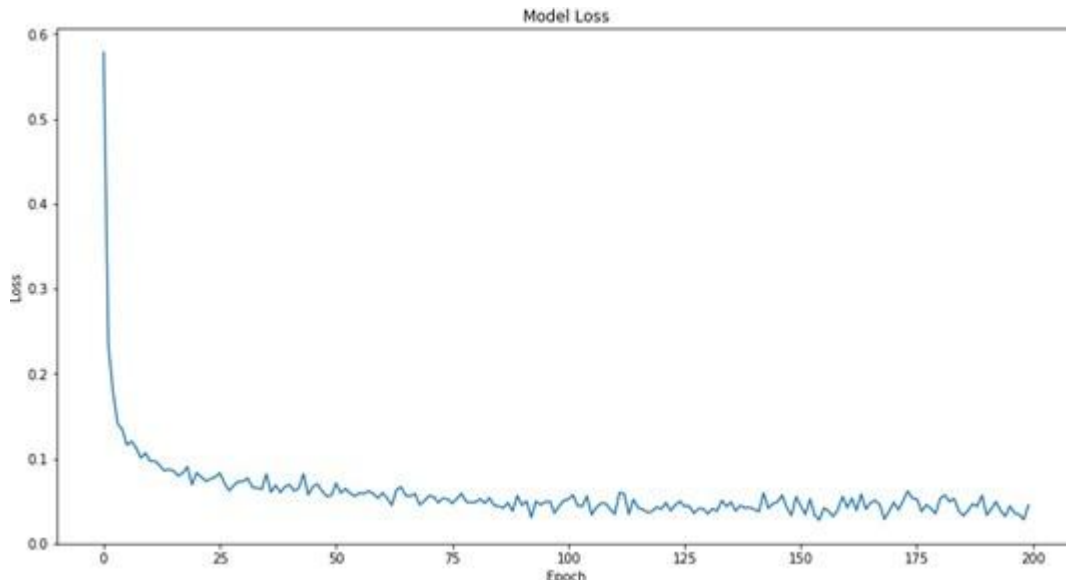**Fig: 4 Comparison of Precision for different models**



**Fig 5: Model Accuracy**

Fig 6: Model Loss

```
# Load Data

Tr = pd.read_csv('UCI HAR Dataset/train.csv')#, sep=",", header=None)

Te = pd.read_csv('UCI HAR Dataset/test.csv')

Tr.head(5)
```

```
In [13]:  pred = test_model(estimator, encoderTe, TeX)

In [14]:  score(TeY, pred)

          Test Accuracy : 99.55%
```

Fig 7: Snippet of Test Accuracy

## IV. CONCLUSION

Human activity analysis is a popular activity in the growing industry and we have applied different machine learning algorithm. Comparative study performed among the applied various techniques kNN, SVM, Random forest, Neural Networks, Logistic regression and Naïve Bayes. In them, Logistic Regression and neural network gave good results whereas Naive Bayes result was not good. The implementation of Neural Network on Python gave better results than the one provided in the Orange tool.The limitations of this work is though the efficiency of neural network is good, the model is not dynamic. The inability of getting trained with real time data will force us to train the model everytime new data comes.In future, these results can be used for making smart watches and similar devices which can track a user's activity and notify him/her of the daily activity log. They can also be used for monitoring elderly people, prison inmates,or anyone who needs constant supervision.

**REFERENCES**:

1. Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, Jorge L. Reyes-Ortiz(2012). Human Activity Recognition on Smartphones Using a Multiclass Hardware-Friendly Support Vector Machine. Springer International Workshop on Ambient Assisted Living.Lecture notes in Computer Science. Vol(7657), pp 216-223.
2. Jun Liu, Amir Shahroudy, Dong Xu, Gang Wang(2016). Spatio-Temporal LSTM with Trust Gates for 3D Human Action Recognition. European Conference on Computer Vision., pp 816-833. Vol(9907) Oyelade, Oladipupo, Obagbuwa(2010). Application of k-Means Clustering algorithm for prediction of Students'
3. Academic Performance. International Journal of Computer Science and Information Security,7(1).292-295
4. JuhaVesanto(1999). SOM-Based Data Visualization Methods. Intelligent Data Analysis, Laboratory of Computer and Information Science, Helsinki University of Technology, P. O. Box 5400, FIN-02015 HUT, Finlandvol. 3(2), pp. 111-126.
5. Ivan Viola(2010). Information Theory in Computer Graphics and Visualization. Proceeding in SA'11SIGGRAPH Asia 2011 Courses.

6.  Jiang, L., Zhang, H., &Cai, Z. (2009). A novel Bayes model: Hidden NaïveBayes.IEEE Transactions on
    Knowledge and Data Engineering, 21(10),1361–1371.
7.  Vincenzi S., Zucchetta M., Franzoi P., Pellizzato M., PranoviF.,De Leo G.A., Torricelli P.(2011). Application of a
    Random Forestalgorithm to predict spatial distribution of the potential yield ofRuditapesphilippinarumin the Venice
    lagoon, Italy. Ecol. Model.222, 1471−1478.
8.  Jie Hu, Yu Kong, Yun fu. (2013). Activity Recognition by Learning Structural and Pairwise Mid-level Features Using
    Random Forest . 2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition
    (FG) Automatic Face and Gesture Recognition
9.  J.K.Aggarwal. M.S.Ryoo.(2011). Human activity analysis: A review. ACM Computing Surveys. 43(3)
10. [10] Enea Cippitell ,Ennio Gambi , Susanna Spinsante, Francisco Florez-Revuelta (2016). Human Action
    Recognition Based on Temporal Pyramid of Key Poses Using RGB-D Sensors. Springer International,
    Conference, Advanced Concepts for Intelligent Vision Systems.PP 510-521.vol(10016)
11. [11] Qingzhong Liu, Zhaoxian Zhou, SarbagyaRatnaShakya, PrathyushaUduthalapally, MengyuQiao, and Andrew H.
    Sung(2018). "Smartphone Sensor-Based Activity Recognition by Using Machine Learning and Deep Learning
    Algorithms" International Journal of Machine Learning and Computing, Vol. 8, No. 2.
12. [12]Ms.S.Roobini, Ms.J.FenilaNaomi(2019). Smartphone Sensor Based Human Activity Recognition using Deep
    Learning Models. International Journal of Recent Technology and Engineering . ISSN: 2277-3878, Volume-8,
    Issue1.
13. [13] Ye, G. Stevenson, and S. Dobson, "Kcar: A knowledge-drivenapproach for concurrent activity
    recognition,"Pervasive and MobileComputing, vol. 19, pp. 47 – 70, 2015.
14. [14] O. D. Lara and M. A. Labrador, "A survey on human activity recognitionusing wearable sensors,"IEEE
    Communications Surveys and Tutorials,vol. 15, no. 3, pp. 1192–1209, 2013.
15. [15]M. Ziaeefard and R. Bergevin, "Semantic human activity recognition: Aliteraturereview,"Pattern
    Recognition, vol. 48, no. 8, pp. 2329 – 2345,2015.