Classifications of Yoga Poses by through Image enhancement CLF Technique

V.Loganathan [1]
N.Suganthi [2]
L.Jenitha Mary [3]
T.A.Mohanaprakash [4]

[1.] Associate professor, Department of Computer Science Engineering, Saveetha Engineering College, Tamil Nadu, Chennai
[2.] Assistant professor, Department of Computer science and engineering, SRM Institute of Science and Technology, Ramapuram Campus, Tamil Nadu, Chennai
[3.] Assistant professor, Department of Computer science and engineering, DMI College of engineering, Tamil Nadu, Chennai
[4.] Associate professor, Department of Computer science and engineering, Panimalar engineering college, Tamil Nadu, Chennai
vadivelu.loganathan@gmail.com [1]
suganthn@srmist.edu.in [2]
jenithagnanadoss@gmail.com, [3]
tamohanaprakash@gmail.com [4]

Abstract:

The calming and stress-relieving effects of yoga are well known. While there are many different yoga positions, the downward dog, goddess, tree, plank, and warrior are among the most well-known. Intelligent technology, which is machine learning, can differentiate between them. As a means to a healthier life, yoga has received worldwide acclaim and praise. It's crucial that you keep your body in the right position at all times while doing a yoga pose. This work explores whether the Naive Bayes Updateable performs well for making classifications of yoga poses. The NBU has the highest accuracy, at 78.33%. LB has 70% accuracy, which is the lowest. NBU has 0.78 precision, the highest among models. LB has 0.70 precision, which is the lowest. NBU's 0.78 recall is the highest among models. The LB's recall is 0.70, which is low. NBU's 0.56 kappa is the highest among models. The LB has the lowest kappa (0.39). NBU's F-Measure is 0.78, the highest among models. The LB has a 0.70 F-Measure, the lowest number. NBU has 0.56 MCC, the highest among models. The LB has a MCC of 0.4, the lowest value. The NBU has the highest ROC, 0.83. The IBK has the lowest ROC, 0.74. LB's 0.82 PRC is the highest among models. IBK has a 0.68 ROC, the lowest PRC. This work finds that the Naïve Bayes Updateable gives best performance compare with other models.

Key terms: Naïve Bayes Updateable, recall, Instance Based Classifier, precision, ROC

I Introduction

Indians of the Indus-Sarasvati civilzation are credited with creating yoga some 5, 000 years ago. The term "yoga" refers to a state of mind in which the mind and body become one.[1-2] Through the practice of asana, meditation, and other methods, it is used to keep the mind and body in harmony despite the inevitable ups and downs of daily life.[3-5] Modern life's stressors have catapulted yoga into the limelight, and now there are a plethora of ways to practice and study the ancient art. Yoga can be studied and practiced in dedicated yoga studios, with private teachers, and independently with the aid of resources such as the World Wide Web, printed texts, video recordings, and other media. [6-8]As a result of time constraints, many people today prefer to educate themselves independently rather than relying on the aforementioned options. Self-study, on the other hand, might not reveal any "wrong" positions.[9-12] A person's health can be negatively impacted by adopting a slouched posture, which can cause both short-term discomfort and long-term, chronic issues. [13-15] Users can choose a yoga pose they want to work on and then record a video of themselves holding the position.[16-18] As with any physical activity, proper execution of yoga poses is crucial to achieving the intended benefits and avoiding injury. According to this logic, it's best to have a yoga teacher there while you practice. In today's busy world, it's not always feasible to study under a yoga teacher or to enroll in group yoga courses.[19-21] Using artificial intelligence, a system can analyze user data to determine which yoga positions they are currently in and then provide comments or recommendations.[22-24] Users are able to benefit from these guidelines and learn how to make their poses more beneficial rather than harmful. The project's difficulties include the need for complete key point detection and the requirement that models maintain accuracy even when body parts are overlapping.[25-26] Incorrect suggestions might have negative outcomes, so it's important to be precise. It is recommended that professionals pose the data sets used in this study. Models should correctly categorize stances, even if they are

practically identical but for a minor detail. In this paper, we create methods based on machine learning to classify the yoga posture.

Here's how the paper continues: discusses yoga pose dataset collection and estimate work. The section describes the datasets and the proposed methods to extract essential features, classify them, and generate feedback. The implementation, evaluation, and analysis are discussed. Finally, the conclusion is discussed.

II Terms and Definition

This section focuses on the dataset description, experimental setup and proposed architecture of this research work.

Dataset Description:

The yoga poses dataset downloaded from the leading data repository such as kaggle repository. There are two directories in the dataset, train and test, with five folders in each directory representing the five categories of yoga postures. Namely, dog pose, goddess pose, tree pose, plank pose and the warrior pose.

The following machine learning algorithms are used in this research work.

- **Naïve Bayes Updateable (NBU):** This classifier will use a default precision of 0.1 for numeric attributes when build Classifier is called with zero training instances.
- **Fisher's Linear Discriminant Analysis function (FLDA):** The threshold is selected so that the separator is half-way between centroids. The class must be binary and all other attributes must be numeric. Missing values are not permitted. Constant attributes are removed using Remove Useless. No standardization or normalization of attributes is performed.
- **Instance Based Classifier(IBK):** In Weka this algorithm is called IBk (Instance Based Learner). The IBk algorithm does not build a model, instead it generates a prediction for a test instance just-in-time
- **Logit Boost(LB):** This class performs classification using a regression scheme as the base learner, and can handle multi-class problems.

The above algorithms are implemented in Weka 3.9.5 by using 10% of testing data and 90% of training data from selected image collections.

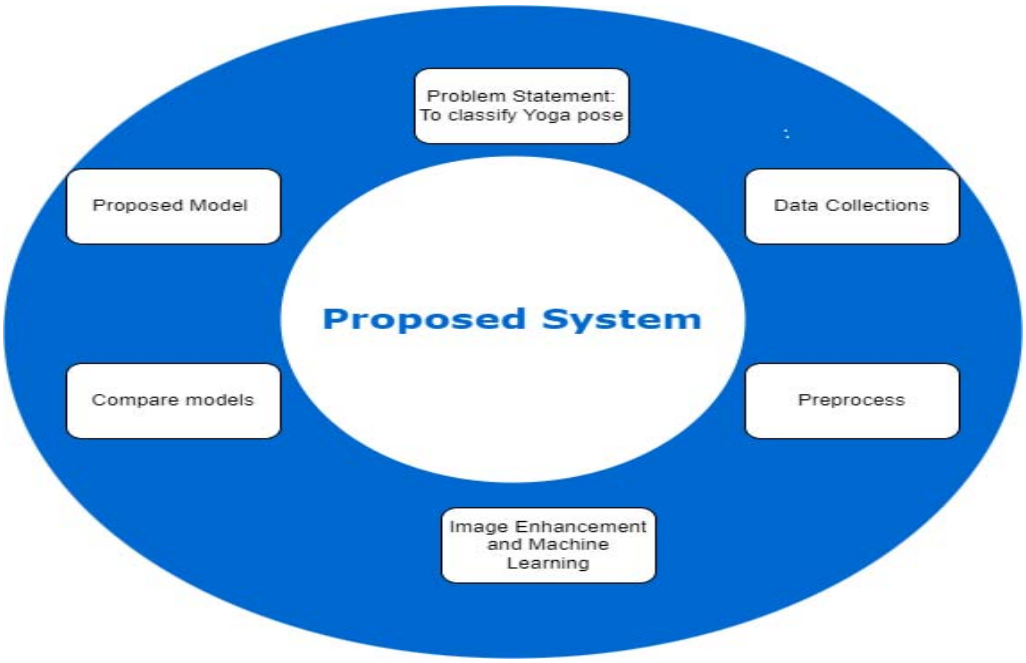

Figure 1: Proposed System Architecture

III Outcome and Interpretation

This section discusses with outcome of the NBU, FLDA, IBK, and LB machine learning. The below table shows that the various performance of selected classifiers.

Table 1: Performance of Selected models

S.No	Learning Model	Time(Seconds)	Accuracy	Precision	Recall
1	NBU	0.02	78.33%	0.78	0.78
2	FLDA	0.2	76.67%	0.77	0.77
3	IBK	0	75.00%	0.75	0.75
4	LB	0.05	70.00%	0.7	0.7

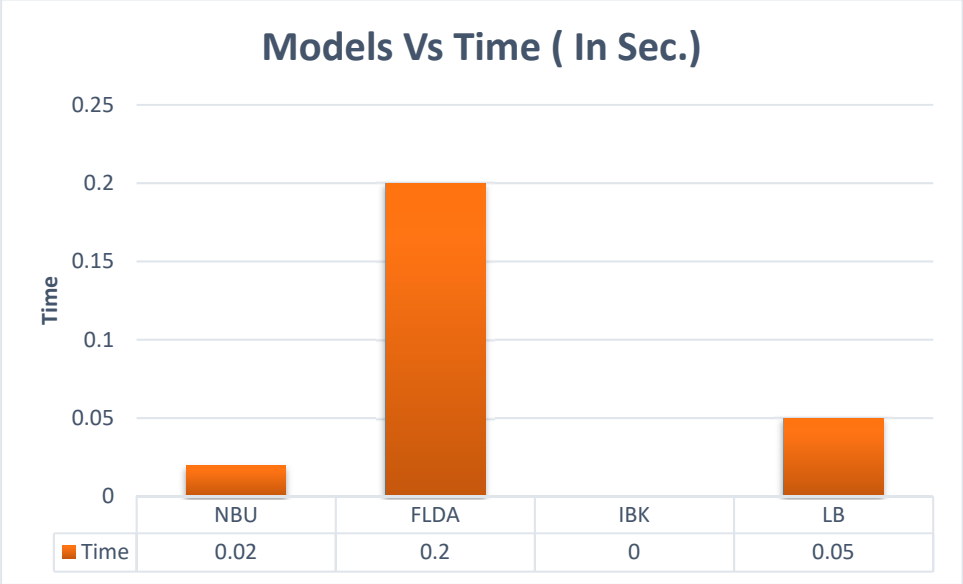

Figure 2: Selected Models Vs Time (In.Sec)

The above figure 2 represents that the selected models and their time consumption performance for making models. FLDA consumes 0.2 seconds for creating model which is highest time consumption for making model compare with other models. The IBK takes 0 seconds for creating model which is lowest time sucking for making model compare with other models. The NBU takes 0.02 and LB takes 0.05 seconds for designing its models.

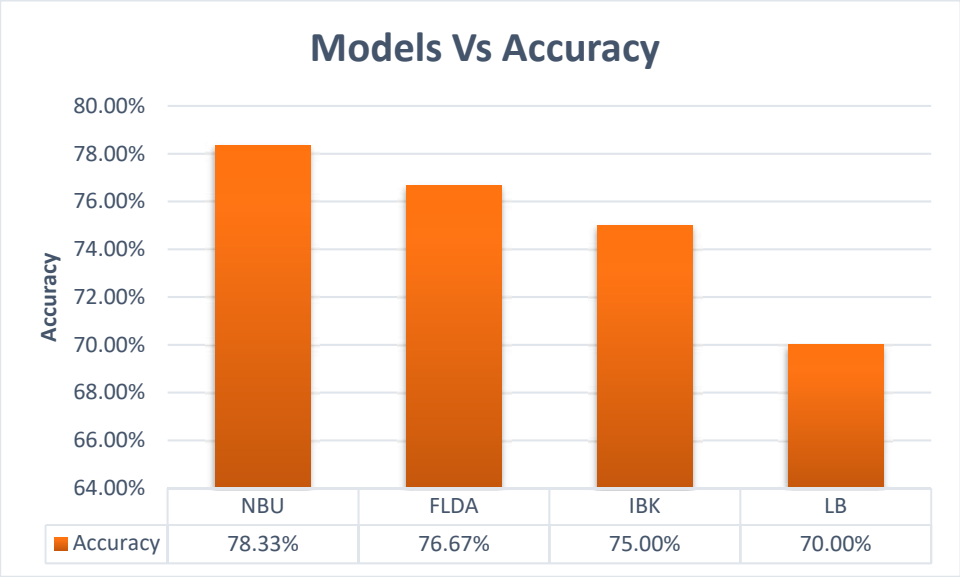

Figure 3: Selected Models Vs Accuracy

The figure 3 shows that the NBU shows 78.33% of accuracy which is largest accuracy compare with other models. The LB shows 70% of accuracy which is lowest accuracy compare with other values. The FLDA and IBK shows 76.67% of accuracy and 75% of accuracy respectively.

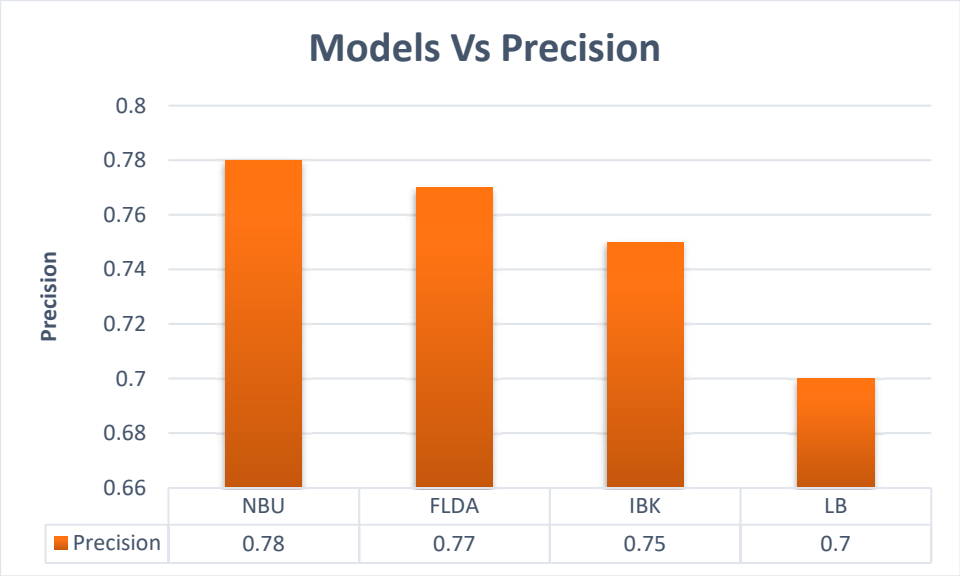

Figure 4: Selected Models Vs Precision

The figure 4 shows that the NBU shows 0.78 which is largest precision compare with other models. The LB shows 0.70 of precision which is lowest precision compare with other values. The FLDA and IBK shows 0.77 and 0.75 of precision values respectively.

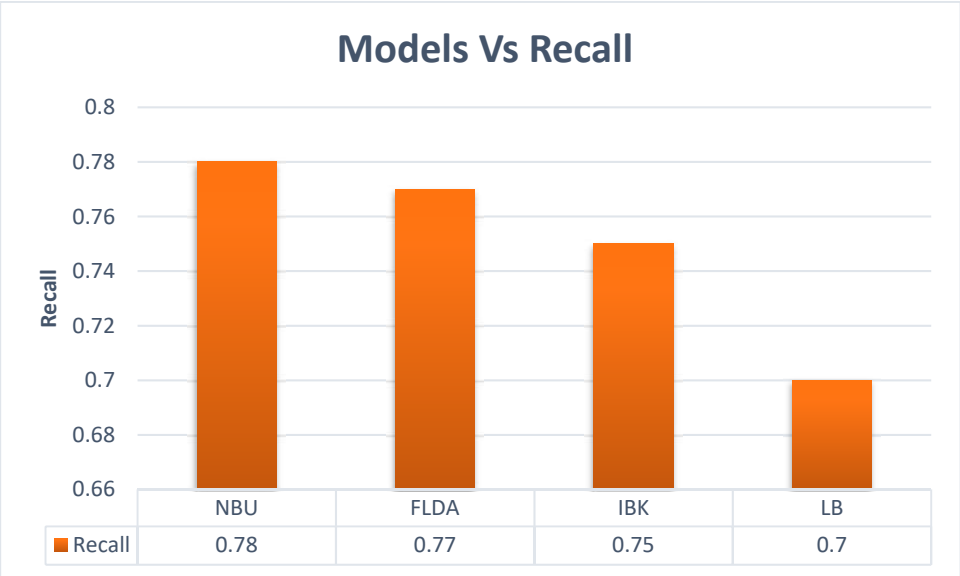

Figure 5: Selected Models Vs Recall

The figure 5 shows that the NBU shows 0.78 which is largest recall compare with other models. The LB shows 0.70 of recall which is lowest recall compare with other values. The FLDA and IBK shows 0.77 and 0.75 of recall values respectively.

Table 2: Performance(Kappa, F-Score, and MCC) of Selected models

S.No	Learning Model	Kappa	F-Measure	MCC
1	NBU	0.56	0.78	0.56
2	FLDA	0.54	0.77	0.54
3	IBK	0.49	0.75	0.5
4	LB	0.39	0.7	0.4

The above table 2 shows that the kappa statistic, F-Measure and Matthews Correlation Coefficient (MCC) values of selected classifiers

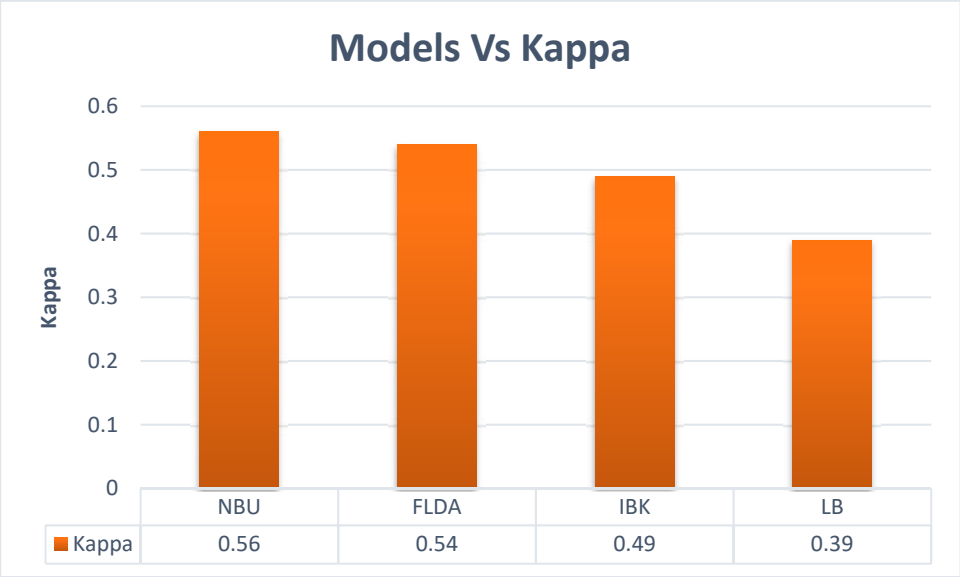

Figure 6: Selected Models Vs Kappa

The figure 6 shows that the NBU shows 0.56 which is largest kappa compare with other models. The LB shows 0.39 of kappa which is lowest kappa compare with other values. The FLDA and IBK shows 0.54 and 0.49 of kappa values respectively.

Figure 7: Selected Models Vs F-Measure

The figure 7 shows that the NBU shows 0.78 which is largest F-Measure compare with other models. The LB shows 0.70 of F-Measure which is lowest F-Measure compare with other values. The FLDA and IBK shows 0.77 and 0.75 of F-Measure values respectively.

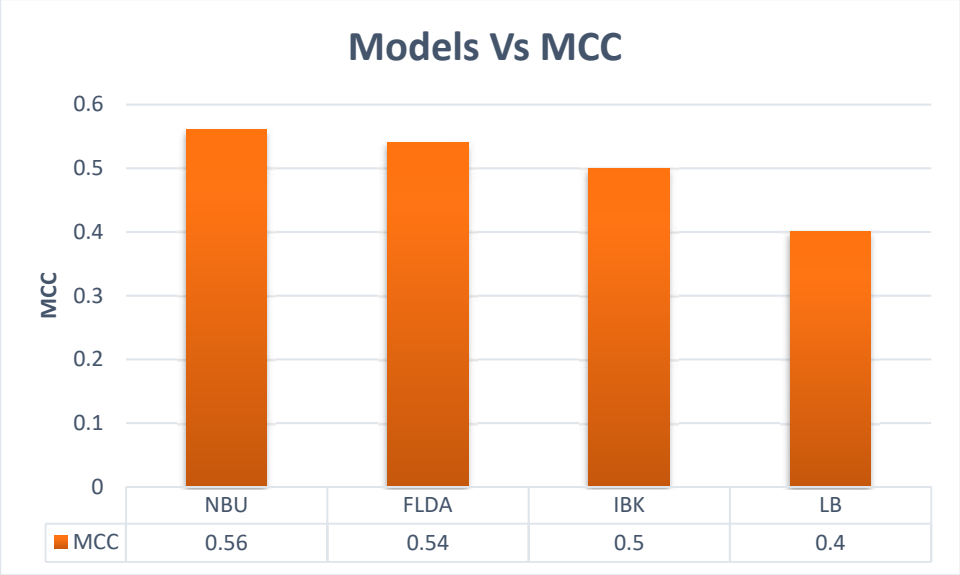

Figure 8: Selected Models Vs MCC

The figure 8 shows that the NBU shows 0.56 which is largest MCC compare with other models. The LB shows 0.4 of MCC which is lowest MCC value compare with other values. The FLDA and IBK shows 0.54 and 0.5 of MCC values respectively.

Table 3: ROC and PRC performance of Selected Models

S.No	Learning Model	ROC	PRC
1	NBU	0.83	0.81
2	FLDA	0.82	0.81
3	IBK	0.74	0.68
4	LB	0.81	0.82

The above table 3 shows that the performance of Receiver Operating Characteristic Curve (ROC) and Precision Recall Curve (PRC) values of selected learning models.

Figure 9: ROC of selected Classifiers in Weka

The diagram shows the distribution of ROC of selected classifiers in weka.

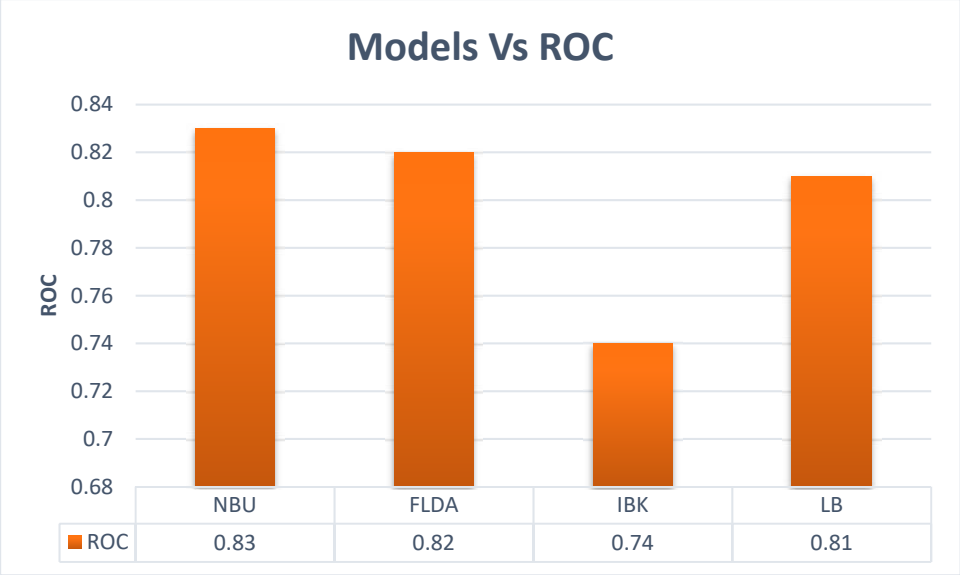

Figure 10: Selected Models Vs ROC

The figure 10 shows that the NBU shows 0.83 which is largest ROC compare with other models. The IBK shows 0.74 of ROC which is lowest ROC value compare with other values. The FLDA and LB shows 0.82 and 0.81 of ROC values respectively.

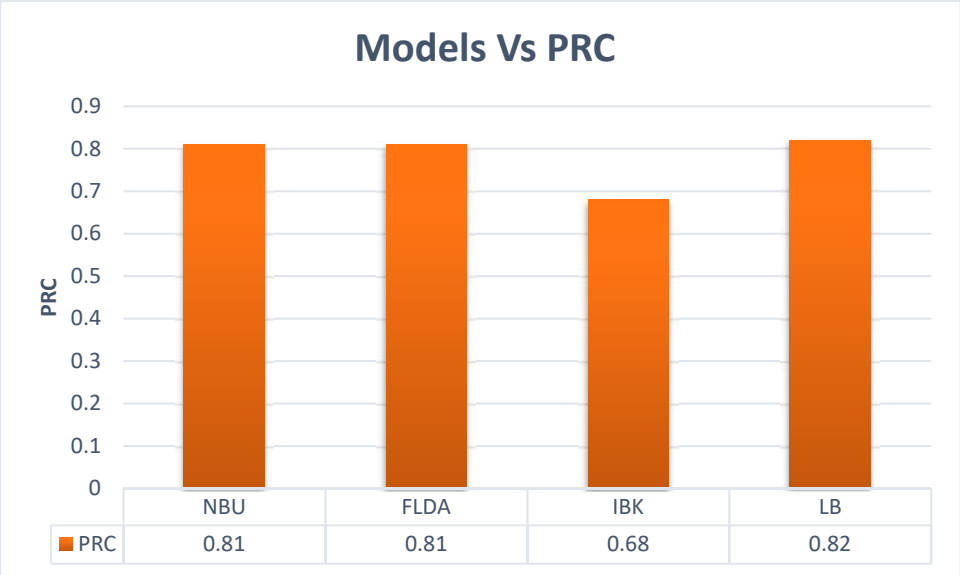

Figure 11: Selected Models Vs PRC

The figure 11 shows that the LB shows 0.82 which is largest PRC compare with other models. The IBK shows 0.68 of ROC which is lowest PRC value compare with other values. The NBU and FLDA shows same PRC which is 0.81 of PRC.

Table 4: Deviation performance of Selected Models

S.No	Learning Model	MAE	RMSE	RAE	RRSE
1	NBU	0.24	0.45	48.09%	90.30%
2	FLDA	0.35	0.42	70.57%	84.20%
3	IBK	0.26	0.49	51.91%	98.28%
4	LB	0.31	0.45	61.52%	89.68%

The above table 4 shows that the deviation performance mean absolute error (MAE), root means squared error (RMSE), relative absolute error (RAE) and root relative squared error (RRSE) values of various selected learning models.

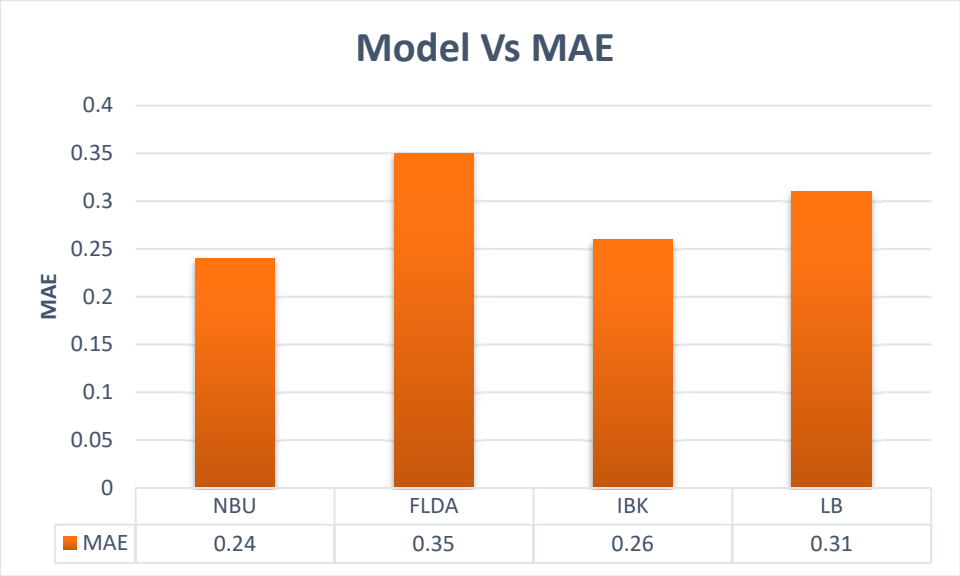

Figure 12: Selected Models Vs MAE

The above diagram 12 shows the NBU shows bets performance which is 0.24 of MAE. The FLDA shows worst performance which is 0.35 of MAE. The LB and IBK shows 0.31 of MAE and 0.26 of MAE.

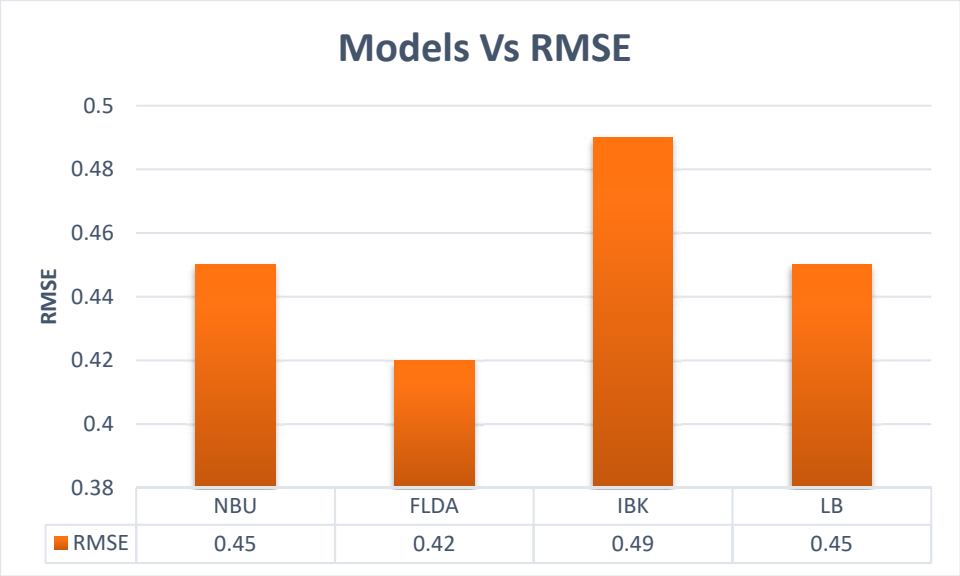

Figure 13: Selected Models Vs MCC

The above diagram 13 shows the FLDA shows bets performance which is 0.42 of RMSE. The IBK shows worst performance which is 0.49 of RMSE. The NBU and LB shows same RMSE value which is 0.45 of RMSE.

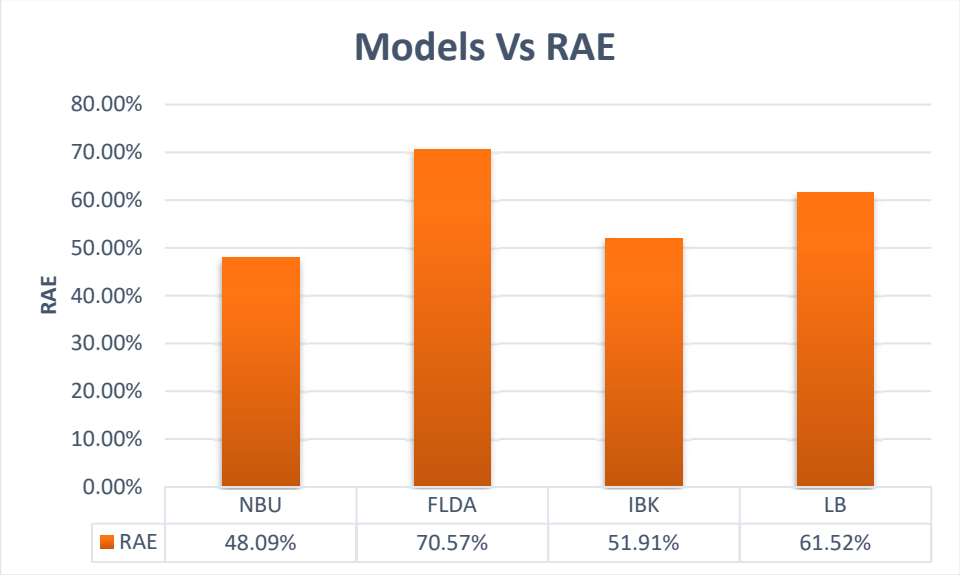

Figure 14: Selected Models Vs MCC

The above diagram 14 shows the NBU shows bets performance which is 48.09% of RAE. The FLDA shows worst performance which is 70.57% of RAE. The LB and IBK shows 51.91% of RAE and 61.52% of RAE respectively.

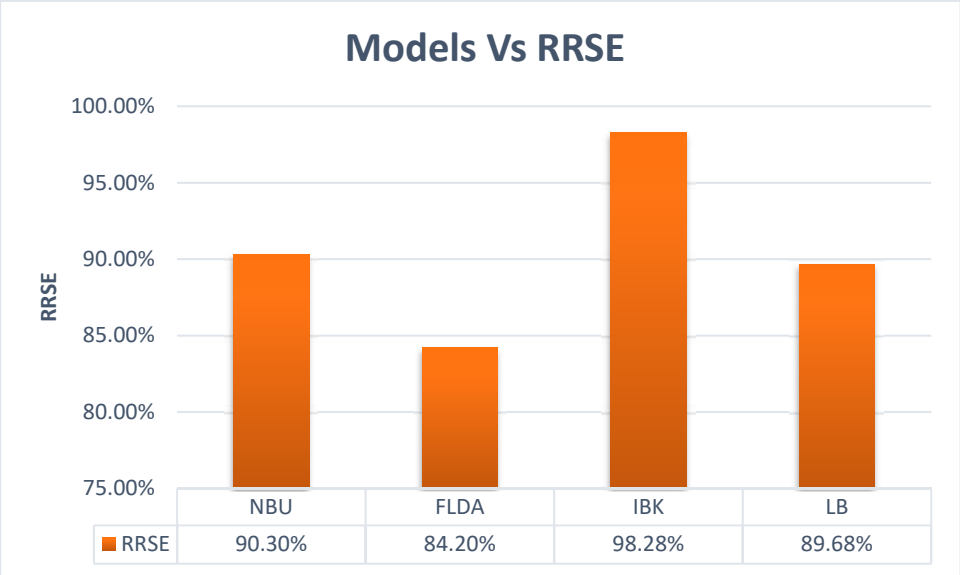

Figure 15: Selected Models Vs RRSE

The above diagram 15 shows the RRSE shows bets performance which is 48.09% of RAE. The FLDA shows worst performance which is 70.57% of RAE. The LB and IBK shows 51.91% of RAE and 61.52% of RAE respectively.

IV Conclusion

This work concludes that the NBU's performance is good compared with other models. The NBU shows best performance, which is 0.24 of MAE. The FLDA shows the worst performance, which is 0.35 of MAE. The FLDA shows best performance, which is 0.42 of RMSE. The IBK shows the worst performance, which is 0.49 of RMSE. The NBU shows best performance, which is 48.09% of RAE. The FLDA shows the worst performance, which is 70.57% of RAE. The RRSE shows best performance, which is 48.09% of the RAE. The FLDA shows worst performance, which is 70.57% of RAE. This system recommends that the Naïve Bayes Updateable produces due to its performance.

Declarations

Conflicts of interest: The author's declare that they have no conflict of interest.

References

[1] Chasmai, M., Das, N., Bhardwaj, A. et al. A View Independent Classification Framework for Yoga Postures. SN COMPUT. SCI. 3, 476 (2022). https://doi.org/10.1007/s42979-022-01376-7
[2] Vivek Anand Thoutam, Anugrah Srivastava, Tapas Badal, Vipul Kumar Mishra, G. R. Sinha, Aditi Sakalle, Harshit Bhardwaj, Manish Raj, "Yoga Pose Estimation and Feedback Generation Using Deep Learning", Computational Intelligence and Neuroscience, vol. 2022, Article ID 4311350, 12 pages, 2022. https://doi.org/10.1155/2022/4311350
[3] https://www.kaggle.com/datasets/niharika41298/yoga-poses-dataset
[4] Li Jiefenf, Wang Can, Zhu Hao, Mao Yihuan, Fang Hao-Shu, Lu Cewu. CrowdPose: Efficient Crowded Scenes Pose Estimation and a New Benchmark. In Proceedings of the IEEE Conference on computer Vision and Pattern Recognition 2019;10855–10864.
[5] Beddiar Djamila Romaissa, Nini Brahim, Sabokrou Mohammad, Hadid Abdenour. Vision-based human activity recognition: a survey. Multimedia Tools and Applications 79, 41 (2020), 2020;30509–30555.
[6] Sun Ke, Xiao Bin, Liu Dong, Wang Jingdong. Deep high-resolution representation learning for human pose estimation. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019;5693–5703
[7] Yu Changqian, Xiao Bin, Gao Changxin, Yuan Lu, Zhang Lei, Sang Nong, Wang Jingdong. Lite-HRNet: A Lightweight High-Resolution Network. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2021;10435–10445
[8] Geng Zigang, Sun Ke, Xiao Bin, Zhang Zhaoxiang, Wang Jingdong. Bottom-Up Human Pose Estimation via Disentangled Keypoint Regression. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2021;14676–14686
[9] Li Jiefeng, Bian Siyuan, Zeng Ailing, Wang Can, Pang Bo, Liu Wentao, Lu Cewu. Human pose regression with residual log-likelihood estimation. In Proceedings of the IEEE/CVF International Conference on Computer Vision. 2021;11025–11034
[10] Li Shichao, Ke Lei, Pratama Kevin, Tai Yu-Wing, Tang Chi-Keung, Cheng Kwang-Ting. Cascaded Deep Monocular 3D Human Pose Estimation with Evolutionary Training Data. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020;6173–6183
[11] McNally William, Vats Kanav, Wong Alexander, McPhee John. Rethinking Keypoint Representations: Modeling Keypoints and Poses as Objects for Multi-Person Human Pose Estimation. In arXiv preprint arXiv:2111.08557 (Accepted to ECCV 2022).2021.
[12] Zhang Feng, Zhu Xiatian, Dai Hanbin, Ye Mao, Zhu Ce. Distribution-Aware Coordinate Representation for Human Pose Estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2020;7093–7102
[13] Liu Zhenguang, Chen Haoming, Feng Runyang, Wu Shuang, Ji Shouling, Yang Bailin, Wang Xun. Deep Dual Consecutive Network for Human Pose Estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2021;525–534
[14] Cao Zhe, Hidalgo Gines, Simon Tomas, Wei Shih-En, Sheikh Yaser. OpenPose: realtime multi-person 2D pose estimation using Part Affinity Fields. IEEE transactions on pattern analysis and machine intelligence 43, 1 (2019), 2019;172–186.
[15] Cheng Bowen, Xiao Bin, Wang Jingdong, Shi Honghui, Huang Thomas S., Zhang Lei. HigherHRNet: Scale-Aware Representation Learning for Bottom-Up Human Pose Estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2020;5386–5395.
[16] Kreiss Sven, Bertoni Lorenzo, Alahi Alexandre. PifPaf: Composite Fields for Human Pose Estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2019;11969–11978.
[17] Zhang Jiabin, Zhu Zheng, Lu Jiwen, Huang Junjie, Huang Guan, Zhou Jie. SIMPLE: SIngle-network with Mimicking and Point Learning for Bottom-up Human Pose Estimation. In Proceedings of the AAAI Conference on Artificial Intelligence. 2021;3342–3350.
[18] Gothe Neha P, Khan Imadh, Hayes Jessica, Erlenbach Emily, Damoiseaux Jessica S. Yoga effects on brain health: a systematic review of the current literature. Brain Plasticity 5, 1 (2019), 2019;105–122.
[19] Gupta Ashish, Gupta Hari Prabhat. YogaHelp: Leveraging Motion Sensors for Learning Correct Execution of Yoga with Feedback. IEEE Transactions on Artificial Intelligence (2021). 2021.
[20] Jain Shrajal, Rustagi Aditya, Saurav Sumeet, Saini Ravi, Singh Sanjay. Three-dimensional CNN-inspired deep learning architecture for Yoga pose recognition in the real-world environment. Neural Computing and Applications 33, 12 (2021), 2021;6427–6441.
[21] Li Yong-Lu, Xu Liang, Liu Xinpeng, Huang Xijie, Xu Yue, Wang Shiyi, Fang Hao-Shu, Ma Ze, Chen Mingyang, Lu Cewu. Pastanet: Toward human activity knowledge engine. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020;382–391.
[22] Maddala Teja Kiran Kumar, Kishore PVV, Eepuri Kiran Kumar, Dande Anil Kumar. YogaNet: 3-D Yoga Asana Recognition Using Joint Angular Displacement Maps With ConvNets. IEEE Transactions on Multimedia 21, 10 (2019), 2019;2492–2503.
[23] Pandit Niharika. New Yoga Pose Dataset. 2020. https://www.kaggle.com/general/192938
[24] Sahni Pooja Swami, Singh Kamlesh, Sharma Nitesh, Garg Rahul. Yoga an effective strategy for self-management of stress-related problems and wellbeing during COVID19 lockdown: A cross-sectional study. PloS one 16, 2 (2021), 2021;e0245214.
[25] Verma Manisha, Kumawat Sudhakar, Nakashima Yuta, Raman Shanmuganathan. Yoga-82: a new dataset for fine-grained classification of human poses. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. 2020;1038–1039.
[26] Yadav Santosh Kumar, Singh Amitojdeep, Gupta Abhishek, Raheja Jagdish Lal. Real-time Yoga recognition using deep learning. Neural Computing and Applications 31, 2019;12(2019),9349–9361.

Authors Profile

Dr. V. Loganathan received his M.E. degree in Computer Science and Engineering from Sathyabama University, Chennai, India in 2012. He has completed Ph.D. in the area of Cloud Security under Saveetha University, Chennai, India. His research interest includes Cloud Security, Big Data. He is having 21 years of teaching experience and Currently he is working as Associate Professor in the Department of Computer Science and Engineering Saveetha Engineering College Chennai.

Dr. N. Suganthi received her B.Tech. degree in Information Technolgy from Pondicherry Engineering College, Pondicherry University, Pondicherry, India in 2005 and M.Tech. degree in Information Technology from Sathyabama University, Chennai, India in 2008. She has completed Ph.D. in the area of Cognitive Radio Networks under Sathyabama University, Chennai, India. Her research interest includes Cognitive Radio Network, Wireless Communication and Networks. She is having 15 years of teaching experience and Currently She is working as Assistant Professor in the Department of Computer Science and Engineering SRM Institute of Science and Technology Ramapuram Campus Chennai.

L. Jenitha Mary, working as an Assistant Professor in DMI College of Engineering. I have 6 years of experience in teaching. I Completed my M.E in Anand Institute of Higher Technology, Kazhipathur in 2013 and B.E in Kamaraj College of Engineering, Virudhunagar in the year of 2008.

Mohanaprakash Thottipalayam Andavan , He received his M.Tech degree in Information Technology from Sathyabama University, Chennai, India. He has 17 years of teaching experience. He is currently working in Panimalar Engineering College, India. He has published more than 30+ research papers in referred international and national journals and 2 patent and 8 copyright. His area of research interest includes cloud computing, Network security and Web Technology.