Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

A TinyML Approach to Human Activity Recognition

To cite this article: Shubham Gupta *et al* 2022 *J. Phys.: Conf. Ser.* **2273** 012025

A TinyML Approach to Human Activity Recognition

Shubham Gupta[1], Dr. Sweta Jain[1], Dr. Bholanath Roy[1]
[1] Computer Science and Engineering Department, Maulana Azad National Institute of Technology, Bhopal, India

Abstract. Human Activity Recognition has been a favorite topic for the scholars not only because of its wide scale acceptance in the industry but areas which may help in medical and in our normal household works as well. Since to make this technology available to the last person standing in the queue it is important that models compiled and trained in this field are not just high performing but optimized as such with incurs the least overhead. And thus bringing TinyML into the picture which has specialty in the field of optimizing the model w.r.t. the size of the model, energy consumption, network bandwidth usage etc. Thus this work includes using optimizing techniques such as pruning and quantization on the pre-proposed models and analyze the changes it causes in such models w.r.t accuracy and size. Our work is able infer that by using both Pruning and Quantization techniques on a human activity recognition model we can compress a model up to 10 time without hampering severe diversion to the accuracy of the model. We have taken three models and UCI-HAR dataset and compare the outcomes of the experiment.

Keywords: Human Activity Recognition, TinyML, Model Optimization.

1 Introduction

Human Activity Recognition (HAR) is basically a classification problem where activities such as walking, laying, standing are considered as classes and are predicted on the basis of user's own data. This research area has the potential to actually build a world which will be fully automated. HAR can find its application in various fields such as Smart-Homes where the user can automate his or her task without being actually present there, in hospitals to monitor the patients without expert supervision, monitoring the activities of the elderly and the children, and many more of such application where automation of tasks is a requirement on the basis of activity of a particular person. So HAR is crucial since it collects and examines user's routine data which helps the systems to support its users [1]. In addition, Human Activity Recognition can also be considered as a prime example of time-series problem [2]. Human Activity Recognition can be carried by different ways but the system depends mainly upon three kinds of devices: wearable sensors [3], video cameras [4], and ambient sensors [5]. Out of these approaches sensor based system has shown dominance for human activity recognition over video based system as the latter has some issues which are mainly related to privacy as well sensors are more sufficive over video-based systems [1]. Plus the cost of installing of sensors-based HAR system is comparatively lesser due to the decreasing cost of the sensors as well as their edge of efficiency being small over the camera based system has attracted more not only the number of research works [6] associated with the sensors but in number of other areas such as devices with carry these sensors such as mobiles, smart-watches etc. [7], in health-care systems[8–10], sports[11], for supporting the specially abled through various mobile systems[12]. Human Activity Recognition is not a new pursued research area, the talks around this topic are at least a decade old and thus many research works have been published centering activity recognition. Earlier the approach of HAR was tried to be achieved through machine learning techniques and which gained a lot of success but these ML methods were mostly hand-featured techniques [13, 14]; and thus these techniques are therefore were proved to be tedious as it involved a lot of human intervention and so it was time taking but most importantly it did not ensure generalization for any kind of un-factored scenarios [15, 16].

Fig.1. Daily Activities

Hence due to the issues stated above there was a gradual shift in the approach from machine learning techniques to deep learning which opened a wide range of research prospects in this field. One of the advantageous aspects of deep learning techniques is that its layered architecture which makes it easy for the model to learn from raw data which has not been preprocessed in any other complex ways and this in turn also helps in scrutinizing the multimodal sensory data in this research field [1]. So the overall reason about why deep learning has been in the center of all the approaches for tackling Human Activity Recognition will that while machine learning algorithms are very much human dependent i.e. a lot of preprocessing will be required before application of the algorithms[17], deep learning models are self-sufficient in distilling knowledge from data which has been directly collected from the sensors[18] without any human intervention and without any prior knowledge of the matter.

Another research area which has been an important part of this work would be TinyML which has been an active research topic not only for the research scholars but also for people in the industry. TinyML has features such as it is power saving [19], secure and fast reactive [20], etc. The actual plan of this research is that to bring Machine Learning models on devices which are require low power to operate and is very low on memory as well, thus increasing the efficiency of the system which involves hardware and connection issues [21]. Thus TinyML will revolutionize the research scope for Human Activity Recognition since these kind of systems needs to be responsive, not dependent upon the internet, cost efficient, etc. and with TinyML on the table HAR research field will now have a wide range of scope which are more environment friendly and reachable to the common folks. This works of ours includes of a deep learning model which is being trained and then various other steps are taken on the trained model to compress the model and prove that the metrics such as accuracy, F1-score etc. of both the original and the compressed model seems to be same. So this paper is further structured into few more sections such as Related Work, Proposed methodology, Results, Conclusion, Future Scope and References.

2 Related Work

2.1 Machine Learning applied to Human Activity Recognition

Over the past few years many algorithms have been applied to human activity recognition which mainly employed supervised learning and were dependent upon human knowledge to extricate high level features. Many of such algorithms were used such as Principal Component Analysis was used in [22], support vector machine in [23], hidden markov model in [24], random forest in [25], in [26] three algorithms were analyzed such as multi-layer perception, J48 and logistic regression. Thus, all of the above mentioned models gave fair results which could be considered acceptable but due to the basic disadvantages of these methods research in this field was kept alive in search for not only better results but which are not limited to the domain knowledge of the human.

2.2 Deep Learning techniques on human activity recognition

Nowadays deep learning is having major contribution towards the activity recognition research area where both convolutional neural network a recurrent neural network has shown great promise in the field. In [27] authors proposed an architecture which consisted of 3-layers of convolution with varying number of filters and results of the work have proved to be successful, again in [28] CNN based models not one but two has been proposed by the author namely CNN-pf and CNN-pff with accuracies over 90%. Just like CNNs, RNNs have also been an attractive approach since works like [29] where a 5-layer stacked LSTM is proposed, a simple but effective architecture where accuracy came up to be around 0.93. In another work [30] a Bi-LSTM based architecture is proposed which achieves accuracy up to 0.94. Not only this many works have taken hybrid models into consideration as well, such as in works like [31] where both the CNN and LSTM have been used together for the activity classification problem and not only this they have compared the model with both single layer LSTM and dense LSTM as well in which the hybrid model is seen to have the edge over the others.

Another hybrid model proposed in [32] which was LSTM-CNN model which seem to have outperform all other models.

2.3 TinyML as a research topic

TinyML is a very new research field and exploring its effects on the other research areas will be an interesting as well as very beneficial stride towards the academia not only in a single but multiple research fields whose disadvantages is being cured by TinyML. One of the works where TinyML has been of help is in [33] where a compressed form of LSTM network namely TinyLSTM is being deployed in the hear-aid device and that has proved to be a successful experiment. TinyML has seen its research progress in mainly speech enhancement techniques, speech separation, denoising etc. but its advantages have not leveraged up to now in the human activity recognition field and that's this will an important step for not only in this field but other areas where blocking points are same which TinyML promises to remove.

3 Proposed Method

In this section we will take two models - a hybrid deep learning model which is DeepConv LSTM and another model with two convolutional layers which will be trained with the UCI HAR dataset and then save the model. We will use the same saved model for further compressing using two different techniques: 1) Pruning and 2) Quantization and thus comparing the metrics of both the models (original and compressed) and reach to the conclusion that if the model trained on the for HAR classification is suitable for the aim which we are pursuing.

3.1 About the model

The models which has been chosen for the experiment is to be used for the experiment are 1. DeepConv LSTM: This model proposed is an example of a hybrid model i.e. a model which leverages advantages of both CNN and RNN and has been a very successful model when accuracy is the metric. Its consists of 4 layers of CNN joined with two layers of LSTM. For more understanding of the model we can look at the fig. which gives details about the model along with its layers.
2. CNN: This is a pure model with two layers of CNN along with a dropout, max pooling and a dense layer respectively to support the model. This model has been a good choice for the scholars for advancing their research in this field.
3. Multi-Layer LSTM: This model is a purely RNN model where one of the most prominent option LSTM has been used with two layers of the same as a single layer lags atleast around 4-5 percent in accurately predicting human activity. This model consists of two layers of LSTM with alternatively placed with two layers of dropout so that the model does not over-fit. All of these models perform fairly well on the dataset which is

used in this work and that is why for comparison purpose and for future research works as well which will help more advances in this field.

Table 1. DeepConv LSTM summary.

Layer (type)	Output Shape	Param #
Conv1D_1 (Conv1D)	(None, 124, 64)	2944
Conv1D_2 (Conv1D)	(None, 120, 64)	20544
Conv1D_3 (Conv1D)	(None, 116, 64)	20544
Conv1D_4 (Conv1D)	(None, 112, 64)	20544
LSTM_1 (LSTM)	(None, 112, 128)	98816
LSTM _2 (LSTM)	(None, 112, 128)	131584
Flatten (Flatten)	(None, 14336)	0
dropout (Dropout)	(None, 14336)	0
Output (Dense)	(None, 6)	86022

Total params: 380, 998
Trainable params: 380, 998
Non-trainable params: 0

Table 2. CNN model summary.

Layer (type)	Output Shape	Param #
Conv1D (Conv1D)	(None, 126, 32)	896
Conv1D_1 (Conv1D)	(None, 124, 32)	3104
dropout (Dropout)	(None, 124, 32)	0
max_pooling1d (Conv1D)	(None, 62, 32)	0
flatten (Flatten)	(None, 1984)	0
dense (Dense)	(None, 50)	99250
Dense_1 (Dense)	(None, 6)	306

Total params: 103, 556
Trainable params: 103, 556
Non-trainable params: 0

Table 3. Multi-Layer LSTM model summary.

Layer Type	Output Shape	Param #
lstm_1 (LSTM)	(None, 128, 32)	5376
dropout_1 (Dropout)	(None, 128, 32)	0
lstm_2 (LSTM)	(None, 32)	8320
dropout_1 (Dropout)	(None, 32)	0
Dense_1 (Dense)	(None, 6)	198

Total params: 13, 894
Trainable params: 13, 894
Non-trainable params: 0

3.2 Pruning

When weights of the neural network are being clipped in such a way that the loss due to shedding of weights is negligible is called pruning. In most of the commonly used neural networks even after being weight-shredded, match its original baseline model and thus it does not incur a significant loss w.r.t. Pruning is basically a process which is iterative and makes use of a trained model and repetitively removes smallest weights over different number of epochs. This technique works because model weights which are unused are being converted to zero and thus un-important paths can be clipped and optimization can take place.

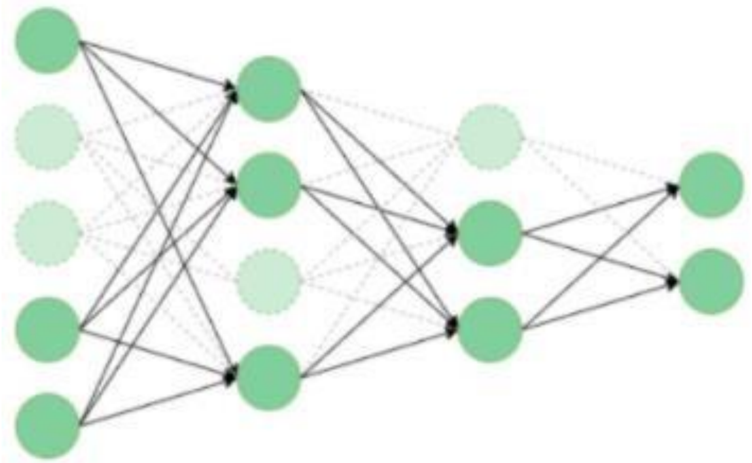

Fig. 2. Structured Pruning

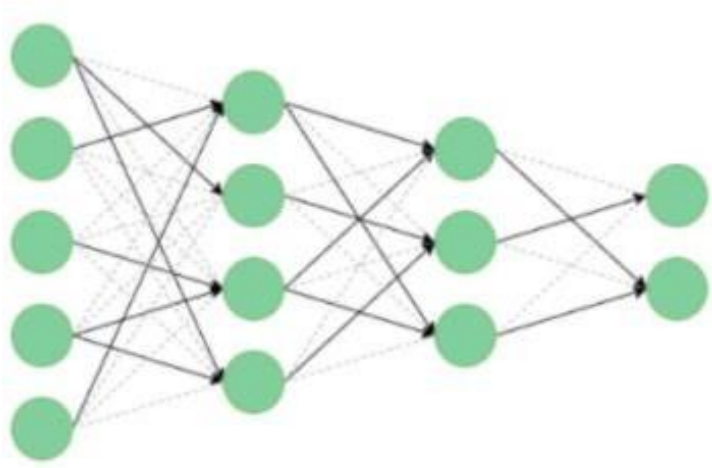

Fig. 3. Unstructured Pruning

There are mainly two types of Pruning techniques
1. Structured Pruning: In this type of pruning technique a whole group or set of weight connection are being removed thus affecting the input and the output shapes of the model. And due to this, a structured pruned model can help a model work more fast than the unstructured but it has some obvious disadvantages since it interferes with the structure of the model.
2. Unstructured Pruning: In this type of pruning individual weights connections are being removed by making those values to 0 and thus these will have no contribution to model behavior at the time of the execution of the same.

Thus in this experiment the amount of sparsity to be clipped is made variable between 50 percent to 80 percent and the best result i.e. show the least diversion w.r.t. accuracy and loss.

3.3 Quantization

The next step in optimization would be quantization which consist of conversion of higher precision values to lower precision such as reducing floating point values to integer values and then after that use integer operations, hence reducing the memory used by the model up-to 4 times, faster computation, less power consumption, reduced bandwidth pressure and integer operations are supported by across different hardware. There are three types of quantization reduced float, hybrid quantization and int quantization (most complex).

Out of the three we have chosen hybrid quantization after checking all the results w.r.t. accuracy, loss and the size of the compressed model.

4 Experimental Setup

4.1 Basic Parameters

To carry out the experiment our model has been trained in keras and tensorflow in the backend and the optimization steps were carried out on Tensorflow lite. For execution purpose Google collab has been used so that many of the issues regarding the dependencies and time taken for the execution is minimal. The dataset used for the model training is UCI-HAR. The batch size used for the training purpose is 16 and is being trained for 30 epochs for the original model training. After that we will train the pruned model for 15 epochs and compare its results with the original model metrics.

4.2 About the Data-set

This is a standard dataset which dates back few years ago and has been a part a lot of experimental scenarios since then. It has mainly six classes out of which the model has to classify. For collecting the data people of varying age from 19-48 with a total of 30 volunteers asked to perform specific task which were - Sitting, Standing, Walking, Lying, Walking-Upstairs and Walking-Downstairs. For all of these activities the volunteers were asked to carry 2 sensors on their body which were Accelerometer and Gyroscope. Thus, for a particular instance there would be 9 raw features which were Acceleration, Gyroscope and full-body acceleration for x,y and z axis each directly collected from the sensors.

5 Results

In this experiment we have tried to examine how a model changes when subjected to compression or in other we can term it as optimization as well as in few steps we have also taken keen note over which optimization step changes what in a model and in the end comparing it with the base model trained in normally without any compression.

We will present out results model-wise such that it is convenient for visualizing the outcomes w.r.t. to each model that has been used for the experiment. Not only this, this will provide a better approach for the analysis process.

1. DeepConv LSTM: So the traditional model works fine and its comes around 91 which proves to be fairly efficient and as pruning is being applied on the model with variable sparsity between 50 percent to 95, means up to these percentages the weights will be shredded and the best accuracy returned between these results. After pruning size of the model has been reduced up to 6 times the original model and a slight increase in accuracy can also be seen. And after the quantization technique model seems to have been compressed up to 10 times and a dip in accuracy is also seen w.r.t. the original model but is negligible. For results refer to table 4.

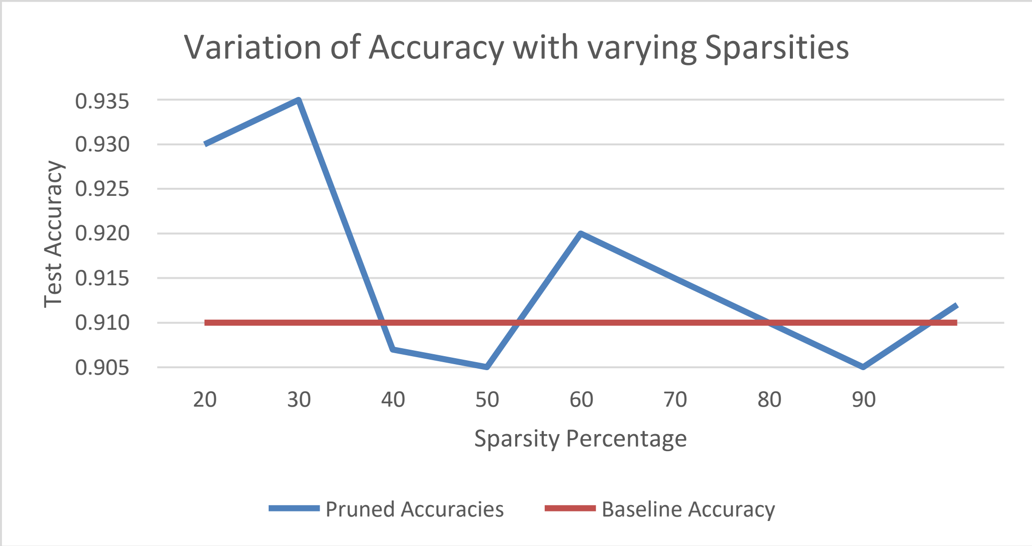

Fig. 4. DeepConv LSTM Accuracy Vs Sparsity

Table 4. DeepConv LSTM Results Summary

DeepConv LSTM	Accuracy	Loss	Size (bytes)
Original Model	0.91414	0.8	956403
Pruned Model	0.9209	0.135	156232
Pruned and Quantized model	0.90486	0.355	49562

2. CNN: This pure CNN model performs decent with test accuracy of around 89 percent which is considered to be efficient in human activity recognition terms and after pruning this works almost not only similar but its accuracy is better by 1 percent and model is compressed up to 3 times and up to 10 times after quantization, thus showing a somewhat inferior results as compared to DeepConv LSTM, but the accuracy seems to be untouched by applying these optimizing techniques. For result summary refer to table no. 5.

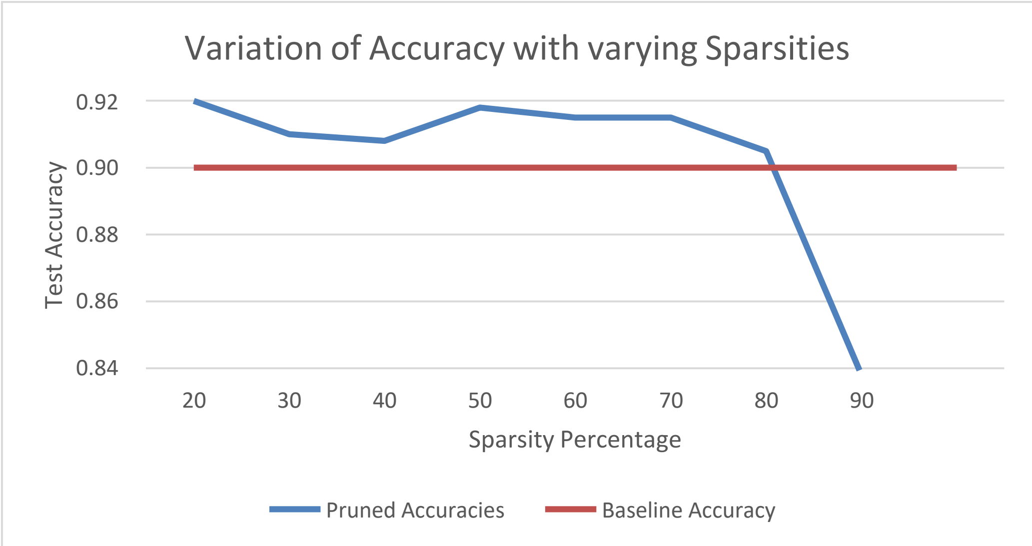

Fig. 5. CNN Accuracy Vs Sparsity

Table 5. CNN Results Summary

CNN	Accuracy	Loss	Size (bytes)
Original Model	0.8965	0.765	387810
Pruned Model	0.9104	0.2158	105965
Pruned and Quantized model	0.8904	0.2586	37729

3. Multi-Layer LSTM: This pure RNN model is a very simple model which proves its worth in the human activity recognition as LSTM works in the field of sequencing and UCI-HAR is a similar kind of time-series data and thus its accuracy comes up to 90 percent which is better than most of the models. But here is an anomaly, after pruning the model size is optimized almost up to 3 times and after applying quantization it compresses up to 4.5 times which different from the above results of the other 2 models. Not only this the dip in accuracy is also slightly more after quantization when compared with the results of the other two models. Refer to table no. 6.

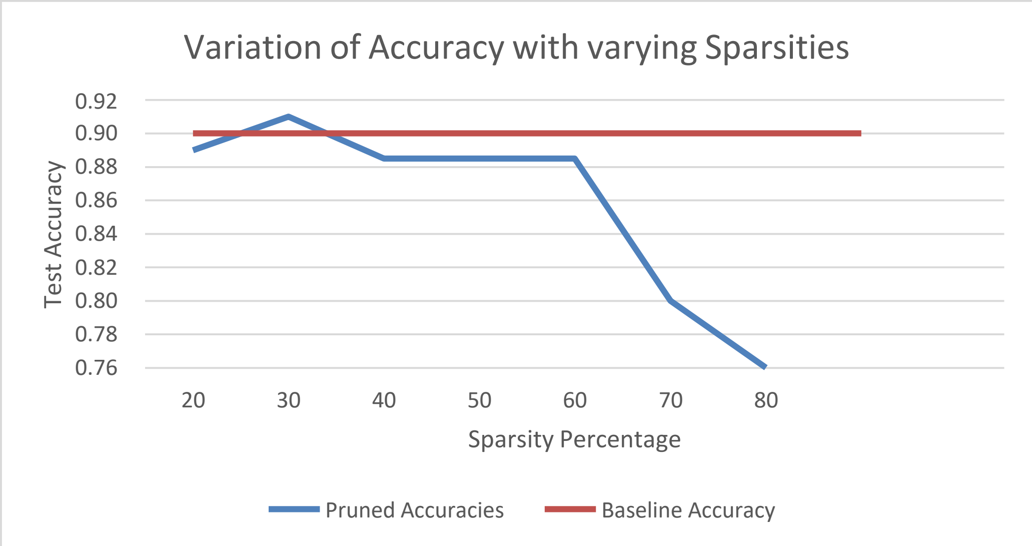

Fig. 6. Multi-Layer LSTM Accuracy Vs Sparsity

Table 6. Multi-Layer LSTM Results Summary

Multi-Layer LSTM	Accuracy	Loss	Size (bytes)
Original Model	0.90566	0.582	54249
Pruned Model	0.90566	0.248	19258
Pruned and Quantized model	0.8892	0.38	12143

Since we have taken three models each with different specifications, it is evident that out work will mostly focus upon the comparative analysis on the models when subjected to model optimization and infer from those results which of those models or which category of those model will be an apt choice for considering Pruning and Quantization techniques. Thus from the results we can infer that the models can be compressed up to at least 4-5 five times and maximum up to almost 20 times without comprising on the accuracy, and also this depends upon the size of the model i.e. larger the model in terms of size more can be its target sparsity and that can be inferred from our work. As we can see DeepConv LSTM is of the largest size its target sparsity is of around 95 percent which is the highest and it can be compressed up to 20 percent but Multi-layer LSTM is small model comparatively and thus percentage target sparsity would also be less. This model starts degrading after achieving 60 percent of the sparsity and achieved compression could be of around just 4-5 times. When we talk about CNN this works fairly well with achieved compression of around 10 times and target sparsity of about 80 percent which was expected as studied from other fields of research. And not only this even the training time of both the original and pruned models differs up to 3 times. For DeepConv LSTM original model training is 213 seconds and for pruned training time is 73 seconds. Similarly, for Multi-layer LSTM original model training is 166 seconds and for pruned techniques it is 52 seconds and for CNN an anomaly can be noticed that for pruned training time is more than original training time which is 56 seconds and 71 seconds respectively.

6 Limitations

Due to having less size in KB or MB in microcontrollers, which is many times less small than even the lowest performing Single Board computers. So it's quite obvious there are limitations in the types of models that can be run with TinyML on microcontrollers as comparison to regular edge ML on more powerful devices like Jetson Nano or Raspberry.

7 Conclusion and Future Work

In this work, we have inferred that the models can be compressed up to 10 times after model optimization for CNN, up-to almost 20 times for DeepConv LSTM and 4 – 5 times for Multi-Layer LSTMs and only not this its accuracy seems to be unchanged up to a point of 80 percent sparsity for CNN, for DeepConv LSTM the point where the model remains unchanged is 95 percent of the target sparsity and for Multi-Layer LSTM it is around 60 to 65 percent but as soon as the target sparsity increases, after this the accuracy (test accuracy) starts degrading, up to 6 percent decrease in each of the model. And that is why, we have used three models for comparison process and check whether which of the model is best suited for the process of model optimization. With all has been done and said there is always a need of new research possibilities within the field and in this field also i.e. human activity recognition new research advances are possible with TinyML approach. New optimization techniques are also on the round and experimenting that with human activity recognition would be an interesting research topic to analyze. Not only this, new variations in optimization techniques such as pruning and quantization would also be a possible research advance in this field thus giving better results by comparing sizes and the accuracies.

References

1. Kaixuan Chen, Dalin Zhang, Lina Yao, Bin Guo, Zhiwen Yu, and Yunhao Liu. Deep learning for sensor-based human activity recognition: Overview, challenges, and opportunities. ACM Computing Surveys (CSUR), 54(4):1–40, 2021
2. Jindong Wang, Yiqiang Chen, Shuji Hao, Xiaohui Peng, and Lisha Hu. Deep learning for sensor-based activity recognition: A survey. Pattern Recognition Letters, 119:3–11, 2019.

3. Jose M Chaquet, Enrique J Carmona, and Antonio Fern´andez-Caballero. A survey of video datasets for human action and activity recognition. Computer Vision and Image Understanding, 117(6):633–659, 2013.
4. Oscar D Lara and Miguel A Labrador. A survey on human activity recognition using wearable sensors. IEEE communications surveys & tutorials, 15(3):1192– 1209, 2012.
5. Charmi Jobanputra, Jatna Bavishi, and Nishant Doshi. Human activity recognition: A survey. Procedia Computer Science, 155:698–703, 2019.
6. Luyang Liu, Cagdas Karatas, Hongyu Li, Sheng Tan, Marco Gruteser, Jie Yang, Yingying Chen, and Richard P Martin. Toward detection of unsafe driving with wearables. In Proceedings of the 2015 workshop on Wearable Systems and Applications, pages 27–32, 2015.
7. Sakorn Mekruksavanich and Anuchit Jitpattanakul. Classification of gait pattern with wearable sensing data. In 2019 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMTNCON), pages 137–141. IEEE, 2019.
8. Lisa Schrader, Agust´ın Vargas Toro, Sebastian Konietzny, Stefan R¨uping, Barbara Sch¨apers, Martina Steinb¨ock, Carmen Krewer, Friedemann M¨uller, J¨org G¨uttler, and Thomas Bock. Advanced sensing and human activity recognition in early intervention and rehabilitation of elderly people. Journal of Population Ageing, pages 1–27, 2020.
9. Sakorn Mekruksavanich. Medical expert system based ontology for diabetes disease diagnosis. In 2016 7th IEEE International Conference on Software Engineering and Service Science (ICSESS), pages 383–389. IEEE, 2016.
10. Sakorn Mekruksavanich and Anuchit Jitpattanakul. Exercise activity recognition with surface electromyography sensor using machine learning approach. In 2020 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), pages 75–78. IEEE, 2020.
11. Lorenzo Porzi, Stefano Messelodi, Carla Mara Modena, and Elisa Ricci. A smart watch-based gesture recognition system for assisting people with visual impairments. In Proceedings of the 3rd ACM international workshop on Interactive multimedia on mobile & portable devices, pages 19–24, 2013.
12. Davide Figo, Pedro C Diniz, Diogo R Ferreira, and Joao MP Cardoso. Preprocessing techniques for context recognition from accelerometer data. Personal and Ubiquitous Computing, 14(7):645–662, 2010.
13. Allan Stisen, Henrik Blunck, Sourav Bhattacharya, Thor Siiger Prentow, Mikkel Baun Kjærgaard, Anind Dey, Tobias Sonne, and Mads Møller Jensen. Smart devices are different: Assessing and mitigatingmobile sensing heterogeneities for activity recognition. In Proceedings of the 13th ACM conference on embedded networked sensor systems, pages 127–140, 2015.
14. Henry Friday Nweke, Ying Wah Teh, Mohammed Ali Al-Garadi, and Uzoma Rita Alo. Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges. Expert Systems with Applications, 105:233–261, 2018.
15. Sojeong Ha, Jeong-Min Yun, and Seungjin Choi. Multi-modal convolutional neural networks for activity recognition. In 2015 IEEE International conference on systems, man, and cybernetics, pages 3017–3022. IEEE, 2015.
16. Tahmina Zebin, Patricia J Scully, and Krikor B Ozanyan. Human activity recognition with inertial sensors using a deep learning approach. In 2016 IEEE SENSORS, pages 1–3. IEEE, 2016.

17. Igor Fedorov, Ryan P Adams, Matthew Mattina, and Paul N Whatmough. Sparse: Sparse architecture search for cnns on resource-constrained microcontrollers. arXiv preprint arXiv:1905.12107, 2019.
18. Yundong Zhang, Naveen Suda, Liangzhen Lai, and Vikas Chandra. Hello edge: Keyword spotting on microcontrollers. arXiv preprint arXiv:1711.07128, 2017.
19. Colby R Banbury, Vijay Janapa Reddi, Max Lam, William Fu, Amin Fazel, Jeremy Holleman, Xinyuan Huang, Robert Hurtado, David Kanter, Anton Lokhmotov, et al. Benchmarking tinyml systems: Challenges and direction. arXiv preprint arXiv:2003.04821, 2020.
20. Jani Mantyjarvi, Johan Himberg, and Tapio Seppanen. Recognizing human motion with multiple acceleration sensors. In 2001 ieee international conference on systems, man and cybernetics. e-systems and e-man for cybernetics in cyberspace (cat. no. 01ch37236), volume 2, pages 747–752. IEEE, 2001.
21. Andreas Bulling, Jamie A Ward, Hans Gellersen, and Gerhard Tr¨oster. Eye movement analysis for activity recognition using electrooculography. IEEE transactions on pattern analysis and machine intelligence, 33(4):741–753, 2010.
22. Tim Van Kasteren, Athanasios Noulas, Gwenn Englebienne, and Ben Kr¨ose. Accurate activity recognition in a home setting. In Proceedings of the 10th international conference on Ubiquitous computing, pages 1–9, 2008.
23. Jennifer R Kwapisz, Gary M Weiss, and Samuel A Moore. Activity recognition using cell phone accelerometers. ACM SigKDD Explorations Newsletter, 12(2):74– 82, 2011.
24. Yuqing Chen and Yang Xue. A deep learning approach to human activity recognition based on single accelerometer. In 2015 ieee international conference on systems, man, and cybernetics, pages 1488–1492. IEEE, 2015.
25. Sojeong Ha and Seungjin Choi. Convolutional neural networks for human activity recognition using multiple accelerometer and gyroscope sensors. In 2016 International Joint Conference on Neural Networks (IJCNN), pages 381–388. IEEE, 2016.
26. Mohib Ullah, Habib Ullah, Sultan Daud Khan, and Faouzi Alaya Cheikh. Stacked lstm network for human activity recognition using smartphone data. In 2019 8th European Workshop on Visual Information Processing (EUVIP), pages 175–180. IEEE, 2019.
27. Peng Zhou, Wei Shi, Jun Tian, Zhenyu Qi, Bingchen Li, Hongwei Hao, and Bo Xu. Attention-based bidirectional long short-term memory networks for relation classification. In Proceedings of the 54th annual meeting of the association for computational linguistics (volume 2: Short papers), pages 207–212, 2016.
28. Ronald Mutegeki and Dong Seog Han. A cnn-lstm approach to human activity recognition. In 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), pages 362–366. IEEE, 2020.
29. Lingjuan Lyu, Xuanli He, Yee Wei Law, and Marimuthu Palaniswami. Privacypreserving collaborative deep learning with application to human activity recognition. In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, pages 1219–1228, 2017.
30. Igor Fedorov, Marko Stamenovic, Carl Jensen, Li-Chia Yang, Ari Mandell, Yiming Gan, Matthew Mattina, and Paul N Whatmough. Tinylstms: Efficient neural speech enhancement for hearing aids. arXiv preprint arXiv:2005.11138, 2020.