SR. NO	Title of the paper	Name of authors	Published year	Remarks
1	Stress Detection with machine learning and deep learning using multimodal physiological data	Pramoda Bobade, Vani M	2018	The objective of the proposed work is to automatically detect the stress condition of an individual by using the physiological data recorded during the stressful situations. **Related work:** In recent years, there are efforts to automate the prediction and detection of stress by machine learning models, which are trained using physiological responses to stress and emotional stimuli. Philip Schmidt had introduced WESAD dataset for the purpose of wearable affect and stress detection and made it available to the public. For collecting this data they had chosen 15 people and recorded the physiological data such as three-axis acceleration, electrocardiogram, blood volume pulse, body temperature, respiration, electromyogram and electrodermal activity by putting wearable devices - RespiBAN Professional and Empatica E4 on the chest and on the wrist respectively. They subjected the subjects to various stress conditions such as baseline, amusement, stress, meditation, etc. They had used and compared the performance of five ma chine learning algorithms for stress state detection: K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), Ran dom Forest (RF), Decision Tree (DT), AdaBoost (AB). They achieved classification accuracies of up to 80.34% and 93.12% considering the three-class (amusement vs. baseline vs. stress) and binary (stress vs. non-stress) classification problems, re spectively, by using common features and classical machine learning methods **METHODOLOGY** Dataset and Features Extraction WESAD is the dataset that is used for this

				study. This dataset was introduced and made publicly available by Attila Reiss, Philip Schmidt, et al. in 2018 . This multimodal dataset is the collection of motion data and physiological fea tures of 15 subjects from both a chest-worn device RespiBAN Professional and a wrist-worn device Empatica E4. Subjects were put into various study protocols such as preparation, baseline condition, amusement condition, stress condition, meditation, recovery, and their physiological stimuli were recorded. Reference [1] describes the details about sensor setup, sensor placement, and the procedure carried out to build this dataset, including which data are collected during which study protocol of the subject. **Preprocessing and Classification Algorithms** Two types of classifications are used-three class and binary classification. Three class classification is defined as classifying an individual as amused, normal or stressed state, whereas, binary classification is defined as classifying an individual as either stressed or unstressed **Results And Discussion** Concluding from this paper, the DT had the overall worst performance, whereas kernel SVM had the best performance among all machine learning classifiers, and ANN gives the overall best performance among all classifiers.
2	A Decision Tree Optimised SVM Model for Stress Detection using Biosignals	AlanaPaul Cruz,Aravind Pradeep, Kavali Riya Sivasankar and Krishnaveni K.S	July 28 - 30, 2020	**RELATED WORKS** In this discussed SVM model to detect stress using ECG as the parameter. QT, EDR and RR were the input features used. The dataset was from Automobile drivers' database. It classifies the output into two categories i.e. Stressed or Not Stressed. The model was first trained with SVM models

				like Linear, Quadratic, Cubic with default kernel function. For training and validation, the Classification Learner app was used which was from MATLAB's Machine Statistics and Machine Learning Toolbox. Accuracy was measured using confusion matrix in MATLAB to find the best SVM model. To find the relevance of the features different combination of features were also used in training. The conclusion drawn was that Cubic SVM model showed higher accuracy rate than other models. Then for further analysis, kernel functions were tuned to improve the performance. In an appropriate feature space, the kernel functions return the inner product between two points and it maps the nonlinear separable dataset into linearly separable one. Here the kernels used for testing were Linear, Quadratic, Cubic and Gaussian. It was found that Gaussian kernel shows higher accuracy level which is shown with the help of Confusion Matrix in Fig. 2. So, from their study it was obvious that Cubic SVM model with a Gaussian Kernel surpassed the other SVM model in accuracy.
3	Machine Learning and IoT for Prediction and Detection of Stress	Mr.Purnendu Shekhar Pandey	2017	**RELATED WORKS** Heart rate variability refers to the beat to beat alterations in the heart rate. According to National Institute of Health, infants generally have a heart rate of more than 100 beats per minute which settles down between 60 to 100 beats per minute (resting heart rate) for children 10 years and older, and adults. Heart rate is directly proportional to a person's fitness . A person who is in good shape will have a resting heart rate in the range of 50-60 bpm compared to an average individual whose heart rate might fluctuate between 60 -80 bpm, whereas a well-trained athlete can have an heart rate as low as 40 bpm.

				Methodology The developed prototype detects whether a person is in stress using variability in his/her heart rate. It can also help in detecting pattern of changes in a person’s heart rate when he/she is working out at the gym. Each device is individual specific and needs to be calibrated for it to function properly. During calibration the person should be in a relaxed mood and should be resting. This is done to set up a baseline after calibration, the device uses this baseline (which is different for every individual) to determine whether that person is in stress/nervous, over trained or currently training. The heartbeat readings are pushed to the server where they are filtered using a user’s network id to keep track of readings for a particular individual. **RESULTS AND ANALYSIS** Stress labels are calculated and median in our data set was stressed and map that to our detector. Further it is not possible to detect someone’s age by their resting heart rate - while some correlations exist, the relationship is not clearly defined. The exercise detection part of our paper does work well because that relationship is clearly defined as 50-80% of the max heart rate (220-Age)

				FUTURE SCOPE This paper provide an insight into the applications of heart rate monitoring and serve as a stepping stone for any new research work in this field. Moreover, the paper faces the challenge of inadequate data, as any machine learning algorithm can only give correct readings/predictions if it is applied on reliable data. Hence, the next step in this work would be to gather heart rate readings of different individuals. We can integrate this work with any health monitoring device and safety device. To get better results, we are using his heart rate and also his daily activity pattern to determine at what time of the day he is exercising and what time he is stressed, as any device can give a false alert when the person is not in danger. One of the most promising future aspects of this work can be to use a person's profile and his daily heart rate measurements along with his galvanic skin response to determine the mood of a person.