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Head Tilting Angle Using Machine Learning

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ABSTRACT

Head tilting angle is determined to be one of the factors that leads to the occurrence of motion sickness among the vehicle driver and passengers. The mathematical model on the relationship between the effect of lateral acceleration and the motion sickness occurrence has been modelled. However, it would be complicated for the vehicle passengers and drivers to put on sensors during a journey leading to the designing of the prediction model of the head tilting angle by using machine learning. Hence, it is very important to have a system in the vehicle that is able to predict the movement behaviour of occupants particularly due to the dynamic changes of vehicle motion in which the model that produce high accuracy results that has yet been established. In order to improve the performance and reduce overfitting occurrence, the implementation of dropout layer is introduced with the variation of hidden neuron numbers in model designing. This work was conducted in order to design a prediction model for head tilting angle of car occupants using machine learning and to analyze the prediction model performance in terms of accuracy with respect to the variation of network parameters. The data modelling went through several stages for modelling and analysis purpose. The parameters are varied in terms of the number of hidden neuron that compromised the single hidden layer in the network. The modelling process are divided into passenger's and driver's model design without and with dropout layer implementation. The results obtained proves that the application of dropout layer in the network modelling improves the accuracy of the output for the passenger's head tilting angle prediction response model but decreasing in the accuracy happens in driver's head roll angle prediction response model due to the RMSE value analyzed. However, the regression values for both driver and passenger's model showed improvement in terms of regression values that proves that the implementation of dropout layer able to reduce overfitting in neural network for non-complex NN architecture.

1. Introduction

The studies on motion sickness and its cause conducted previously based on the published journals available on the web and U.S National Library of Medicine found that nearly everyone is vulnerable to motion sickness, and one in three people is considered to be highly susceptible [1]. A substantial part of the population has encountered motion sickness at some point in their lives in

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which mainly in the form of carsickness or sea-sickness [2]. This statement is supported with a report where 2 out of 3 of individuals have been reported to have endured with motion sickness in cars in which is commonly referred to as carsickness in an autonomous context [2].

The cognitive task, in which the abilities of the mental in hazard evaluation, demands' processing, route planning ability is reduced with the increasing of motion sickness [3]. These conditions are considered as the limitations in human judgement especially in low level automation.

Despite being a common phenomenon for centuries, little improvement in terms of advancement on how to reduce the occurrences of motion sickness had been made for the general human population [1]. In vehicle for instance, analysis on the driver head tilt angle has been made by Wada [6] in terms of mathematical modelling. The results of the passenger and driver's head tilting angle obtained are inconsistent with the findings of Fukuda [13] and Zikovitz and Harris [14] which stated that the head tilting angle of passengers often opposed the drivers' head tilting angle due to the difference in road condition used during the experiment.

The research was later expanded by Saruchi *et al.,* [16] by modelling the correspondence of lateral acceleration and head movement by using artificial neural network. This is in order to prevent the use of sensors from being an essential need in determining the head tilting angle in real life implementation [4]. Thus, the implementation of Radial Basis Function Neural Network was proposed as the method in designing the head roll prediction model for the vehicle occupants and the model output response had provided a successful prediction model [4]. However, the model did not specify the results in terms of accuracy in which later brought to the further work in which ANN was used as the modelling method, specifically focusing on the effect of the hidden neuron numbers corresponds to the accuracy of the designed model.

Nevertheless, the parameters could be varied by implementing the dropout layer in designing the model. The dropout layer implementation able to reduce overfitting in deep neural network [5]. It is believed that dropout layer application could reduce overfitting in non-complex ANN and at the same time improves the model prediction accuracy.

1.1 Machine Learning

Machine learning is an experience-based computational approach for improving efficiency or making an accurate prediction [7]. In this case, experience is the past information that are available for the learner in which usually in the form of collected electronic data that available for analysis. The quality and quantity of the data are crucial for the prediction result's successfulness.

There are three types of machine learning; supervised, unsupervised and reinforcement learning in which each of them functions differently. The supervised learning is defined as a method which the annotated training data are available. In this method, a set of input variables will be mapped onto the output variables in data learning [8]. The name invokes the notion of a 'supervisor' in which instructing the learning system the labels to correlate the with the examples of training [8]. Its main function is to predict the outcome of the future incidence given the input data. Supervised learning consists of regression, classification, naïve Bayes, random forests and several other model types. The distinction in the form of output has resulted to a naming convention for the prediction tasks, in which the regression is used in order to predict the quantitative outputs, while the classification is used for qualitative output prediction [9]. However, both tasks have a great deal in common, particularly in approximation function task.

Unsupervised learning explores on how the systems' ability to learn in a way that represents the statistical structure of the overall input pattern set to represent individual input patterns [10]. The learning algorithms are unlabeled in which will leave the structure of input data to be self-configured as it functions by configuring the data's hidden structure. Unsupervised learning consists of clustering and dimensional reduction. Clustering is a method in which the process of an organization where the similar data will be clustered or also known as grouped together. It is implemented in various field including targeted marketing while dimensionality reduction can be seen used in big data and structure discovery. The clustering itself could be expanded into several algorithms, which is exclusive clustering, overlapping clustering, hierarchical clustering and probabilistic clustering.

Reinforcement learning falls under one of the types of machine learning. It is a system in which should execute a certain goal by interacting with a dynamic environment. The system receives feedback as it navigates the problem space in terms of incentives and penalties. It is implemented in several problems such as in robot navigation and making real time decision.

Each of the types of learning has its own advantages despite facing several limitations that could not be overcome in the time being. Hence, the types of learning must be chosen wisely as to obtain a result with high accuracy.

1.2 Neural Network

Neural network is one of the models that could be categorized as both supervised and unsupervised learning. However, supervised learning has its own advantages as the characteristics of unsupervised learning in which the data are unlabeled which raises question in terms of data meaningfulness.

Artificial Neural Network (ANN) has several advantages including the ability to train data in which the network will learn from the data as an example to be used in order to provide output when similar event occurred [11]. The ANN structure mimics the human basic working unit of brain which is the biological neurons structure. The neurons are the cell that located within the human nervous system that provides human with input the data to be sent to the brain for processing or the medulla oblongata in order for the parts of body to produce a response in conducting activities or survival. A neuron contains four basic structures named as synapse, dendrite, soma and axon in which these structures are imitated in the ANN mathematical model structure as illustrated in Figure 1. Synapse functions as the connector that allows the transmission of impulses carried from one neuron to another in which in ANN model the synapse considered as weight. The dendrites are considered as the summing functions in this model as it imitated the neurotransmitter binding process that require accumulations of the stimulus that called neurotransmitter. Soma is the classified as the body of the neuron in which it receives the stimulus in order to regulate the cell activities that fits to the role of activation function. The last structure which is axon is considered as the output by assuming this model has an axon to axon synapse.

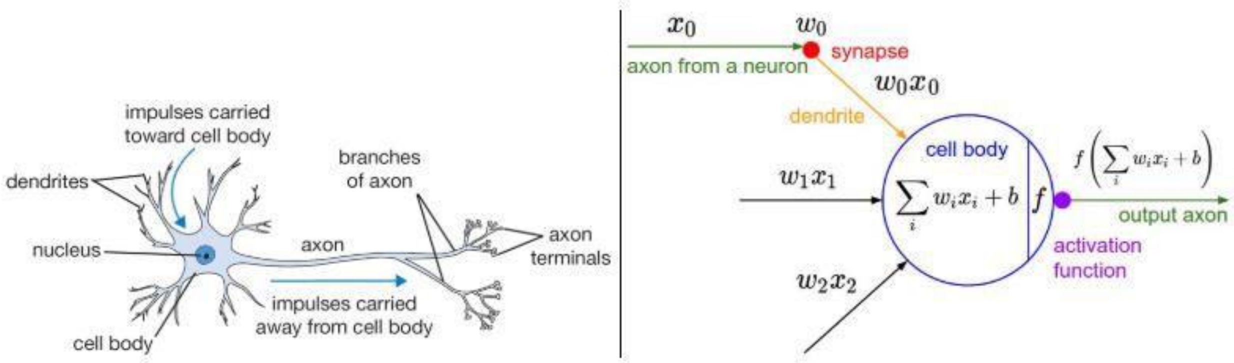

Fig. 1. Comparison between biological neuron and mathematical model neuron [12]

The similarity of the structure of human biological neuron and mathematical model of the neuron that used in ANN leads to the factor that this model is widely known in data modelling in various field.

1.3 Motion Sickness Mitigation

Motion sickness is an incidence where the occurrence of an unpleasant state of discomfort due to the motions' exposure. It is characterized by a malaise feeling and several symptoms, including sweating, pallor, dizziness, nausea and finally vomiting [15]. Motion sickness is one of the symptoms caused by head tilting angle among the vehicle occupants. In an automotive case, it has been reported that 2 out of 3 of people have suffered from motion sickness in cars according to Reason and Brand in 1975, often referred to as car-sickness [1].

Hence, several ways of reducing the occurrence of motion sickness has been proposed as a solution as consuming medication to ease the sickness feelings would be unnatural. D'Amour *et al.,* [19] proposed that seat vibration and airflow as an effective way to mitigate motion sickness occurrence. The studies had found that the head vibration would reduce the severity of motion sickness. However, this method is only applicable with the airflow.

Head tilting angle is believed to be one of the causes of motion sickness in moving vehicle [6]. The disparity in passenger and driver head tilt with respect to the lateral acceleration direction influence the degree of magnitude of the MS occurrence [16]. Saruchi *et al.,* [16] also stated that the driver is less susceptible to *motion* sickness compared to the passenger due to the head tilting angle during a curvature. This is due to the head movement of the passenger that always opposite to the driver in at a curve in which the driver is always tilt the head against the lateral acceleration when experiencing a curve during driving.

According to the Newton Second Law of Motion, force is due to the mass and the acceleration of the object. In vehicle instances, the car acceleration and mass affect the forces acting on the moving car causing the head movement during a curvature. The head movement of the driver was assumed to have a relationship to the decreasing of the carsickness likelihood [6]. The head movement or tilting angle is believed as one of the factors contributing to the occurrence of motion sickness that might cause nauseous feeling and fatigue to people who are prone to it. This could further cause the occupants' discomfort in the journey.

Because passengers tend to be more susceptible to carsickness than drivers, it is assumed that the driver's head movement is related to a decreased likelihood of carsickness and a corresponding increase in comfort. However, it would be tedious for the passenger and driver to put on the sensor every single time riding a vehicle.

Hence, it is very important to have a system in the vehicle that can predict the movement behaviour of occupants particularly due to the dynamic changes of vehicle motion in which the model that produce high accuracy results that has yet been established. Due to dynamic changes of the vehicle motion, it is also important to have a model with a good generalization in order for the model to be able to adapt to a more robust data input in which at the same time able to produce an accurate result.

One of the gaps are able to be determined from Saruchi *et al.,* [16] research in which the studies focused on the number of hidden nodes. Hence, based on the Root Mean Square Error (RMSE) and regression value presented in that experiment, it seems that the model could be improvised in terms of accuracy and fitting by including certain parameters such as the training algorithms, regularization and the types of activation function used. This is important as the parameters influenced the accuracy in neural network prediction model [17].

The objectives of this study are to design a prediction model for head tilting angle of car occupants using machine learning as well as to analyse the prediction model performance in terms of accuracy with respect to the variation of parameters.

The demands in vehicle that could provide a better journey experience justifies the necessities for an improvement of the vehicle system and dynamics. Thus, the solution to the root of the problem is determined as a starting point for the implementation in the bigger process. The head tilting angle prediction model will be used in vehicle control system as an effort to reduce the motion sickness occurrence. This model will produce the prediction of the head tilt as an output with accuracy, in which could be obtained by analyzing the difference in the output produced by varying the network parameters which is the dropout layer. Thus, an accurate model of head tilting angle might be able to be achieved while improving the model generalisation.

2. Methodology

In designing the prediction model for the head tilting angle, MATLAB software is used as the software to training the model. It is chosen as it provides useful data and text analysis tools for the users as well as the features for machine learning [18].

2.1 Neural Network in MATLAB

Neural network model is used in this prediction model design as an extension of the previous work by Saruchi *et al.,* [16] on the correlations of lateral acceleration and head movement's modelling that utilize artificial neural network that focuses on the number of hidden nodes. In MATLAB software, there are four types of neural network available in the toolbox in MATLAB R2019a which are NN clustering, NN fitting, NN pattern recognition and NN time series in which each of them serves different purposes.

ANN has the ability to be trained by learning from the previous events other than its ability in parallel processing that enable the more than one functions to perform simultaneously [11]. By using ANN specifically neural net fitting provided in the MATLAB software, the regression value and RMSE value could be analysed for the model accuracy and performance.

2.2 Data Acquisition Method

The data is obtained through the same process as conducted by *Saruchi et al.,* [16]. In this process, the data on vehicle's lateral acceleration and the movement of the passenger and driver's head was collected.

The track for the testing were set up by arranging six cones along a 150 meter-straight normal road in a manner where the cones were set 20 meters apart for providing obstacle purpose. The participant which consists of ten healthy adults with a valid driving license were instructed to drive in a slalom manner with a constant velocity of 30 km per hour. The track conditions are illustrated as in Figure 2.

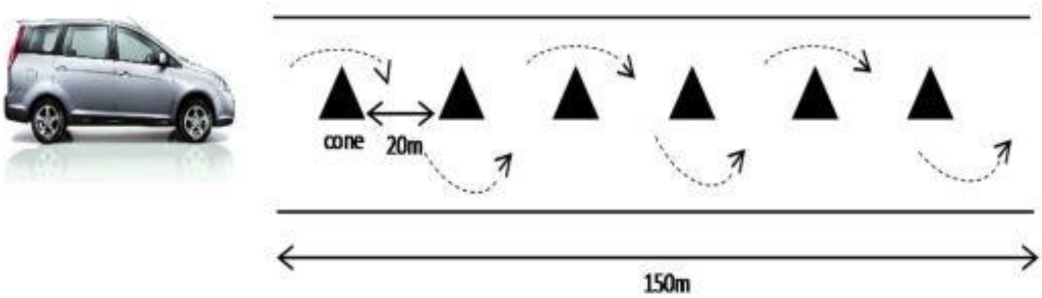

Fig. 2. Illustration of test track conditions [16]

During the test, the driver and passengers were required to naturally tilt the head at a curve. In this test, each of the participants are assigned as both passenger and driver that will be conducted at different time for each of the assigned role. When the participants play the driver role, the participants are prohibited to tilt the head towards lateral acceleration or against the centripetal direction on purpose while when the participant plays the passenger role, the same instructions were given with different way which is to not to tilt the head in opposition to the lateral acceleration or in the direction of the centripetal direction. Before conducting the test, the sensor was checked in order to make sure it is well-functioning and the participation of participants with illness feeling was forbidden during the health checking process and confirmations. The driver and passenger were also required to put on the safety belt and at a curvature, the participants were instructed to tilt the head normally other than prohibited from performing any other activities in order to remain focused.

During the test, the passenger was seated at the front passenger seat while driver was seated at the driver's seat. In this phase, the response of the output produced by the sensors were closely monitored in order to prevent any occurrence of technical error. The driver was instructed to drive the vehicle at a constant speed of 30 km/h and by the time the first cone was reached, the driver was supposed to start driving in a slalom manner along the 150 meter track.

Each of the drivers repeated the slalom drive test thrice. All of the participants were permitted to undertake some practice runs before starting the real test for the familiarity to the slalom path. Overall, each of the participant will experience the role of the driver and passenger thrice for each role. Thus, 30 datasets for each driver and passenger obtained with 10 persons as participants. This acquired data will be used for the process in prediction model designing.

Stage 1: Data division

In this stage, the gathered data are divided into two parts which is for 90 % used for training and 10 % for generalization purpose. This is in order for the model designed able to be tested on unseen data later. This data acts as if the real-life data implementation after the model is chosen.

The generalisation data are not being used in this stage. However, the training data are later divided into 3 parts in which 70 % for training, 15 % for validating and another 15 % for testing during the model training.

Stage 2: Data training

The method proposed to design the head tilting angle prediction model is by using Neural Network. Figure 3 shows the ANN model structure configuration which consists of the interconnection between the input layer, hidden layer and output layer, where the interconnection strength is considered as weight that will be adjusted during the data training. The parameters for the input layer and output layer is only one which is the lateral acceleration and the head roll angle respectively while the number of neurons in hidden layer was varied between one until twenty.

Note that the data training for the passenger's head roll angle and the driver's head roll angle will be conducted separately in which for the driver, the lateral acceleration, ay of the vehicle is the parameter used for the input and the driver's head roll angle, θH_D is the parameter used for the output while the input and output parameters used in order to train the data of the passenger were the vehicle's lateral acceleration, ay and the head roll angle, θH_P of the passengers.

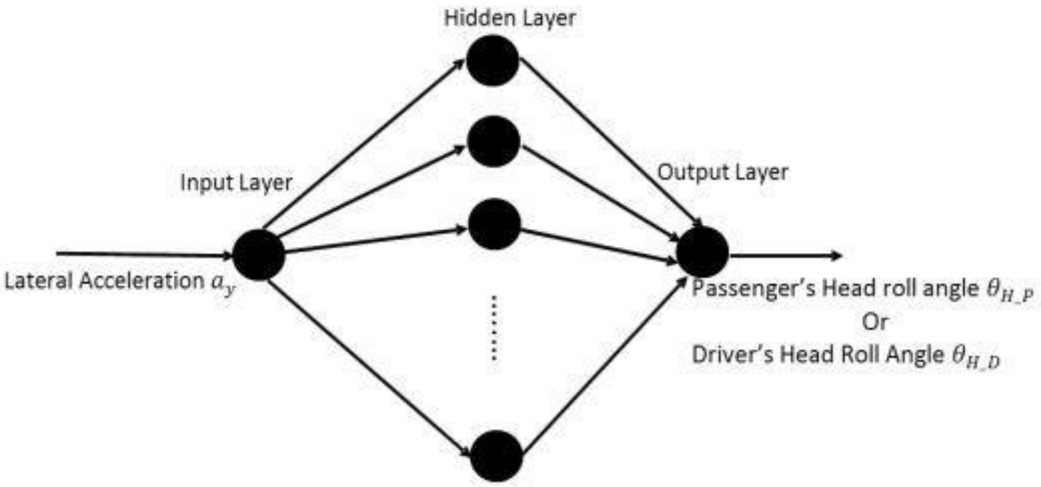

Fig. 3. ANN layer configurations [16]

In training stage, the NN model will first be chosen. The NN model chosen for this prediction data training is neural net fitting as it maps the output based on the input value presented in which in this case, the input is the vehicle LA that will produce the output of HRA. The input and output data are selected and the training data are divided into three parts; training, validation and testing in which each part play different important role in data training. The training sample is used to be presented during training in order for the network to adjust to the error while the validation sample serves the generalization purpose as well as stopping the training process once the data stops generalizing while testing generally serves the purpose of measuring the network performance independently.

After the data division, the number of hidden neurons to be applied in the model are selected. Then, the types of algorithms are selected in the NN toolbox with three main options; Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient. These algorithms could be adjusted in the advanced MATLAB script generated after the first training. However, LM algorithm is chosen in this work as it provides faster convergence rate. The model is later being trained and for the results to be produced.

The number of hidden nodes in the hidden layer is specified at the hiddenLayerSize. Hence, the values are varied between 1 to 20 during training both the driver and passenger's model with and without dropout layer application. The modelling process produced a model architecture as shown in Figure 4.

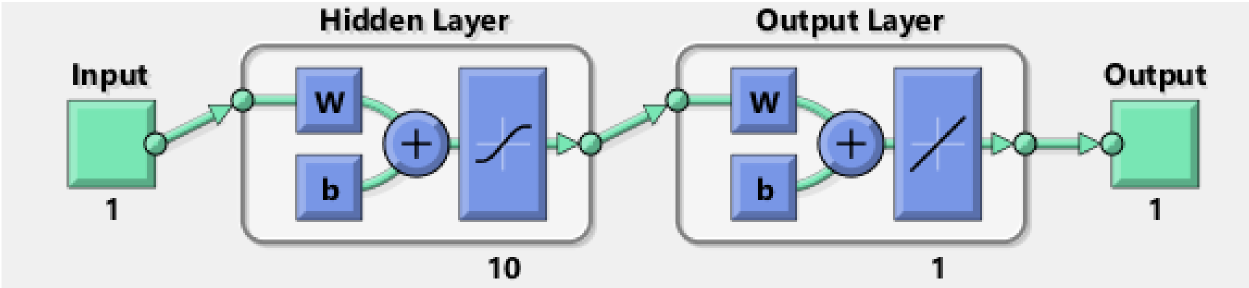

Fig. 4. NN architecture

The parameters used plays an important role in data training to prevent overfitting or under fitting of the data trained for a better model in terms of accuracy. The parameters in this model are stated as in the Table 1 below:

Table 1
Parameters settings in Neural Net Fitting

Parameters	Descriptions
Neurons in hidden layer	Since there are no specific formulas in determining the number of neurons in hidden layer, the trial and error methods are implemented. However, it is important to make sure that the number of neurons are not too small or big as neuron is highly sensitive. Hence, the number of neurons chosen varies between 1 - 20. This is in order to prevent the data from overfitting that lead to the inability of the prediction model to predict an output when the input data is slightly different from the trained data or under fitting in which the data inability to predict the output data precisely.
Number of hidden layer	The number of hidden layer throughout the experiment are kept constant for a more concise analysis. The hidden layer chosen is 1 as this model is considered as a simple problem that require non- complex architecture. To add, this is in order to observe the effectivity of dropout layer in non-complex NN modelling.
Training algorithm	Up to this date, there are 9 types of training algorithms provided in MATLAB software [22]. However, in order to maintain the training efficiency, LM algorithm is used throughout this work.
Regularization	The types of regularization used is dropout layer while another model is specified. This is in order to analyze the difference upon the implementation of dropout layer in the model. The probability of the dropout layer is set to 0.5 throughout the training.
Maximum iteration	The value of maximum iteration number will be fixed throughout the data training which is 1000 iteration. However, the iteration will stop when the model trained stops improving.
Weight and bias	The weight and bias value are not specified as to serve the purpose of training which is to get the optimum value of weight and bias. In this case, the network itself will adjust the parameter of weight and bias in order to achieve the desired output [23].

Stage 3: Results data collection for model analysis

After the data being trained, the values of the output such as RMSE values in which shown in terms of performance and regression values are collected. However, in this stage, the validation performance and regression value for all are analyzed. The model is trained 5 times for each hidden node increment. The average value determined the best model later.

Stage 4: Model testing

The designed models are tested at this stage with the unseen data. At this stage, the generalized data that had been put aside at the first stage are used as the unseen data. This is in order to test the ability of the designed model to generalize to the new data provided. In this stage the codes are generated in order to call the related files for testing purpose.

3. Results and Discussion

The results of the comparison of RMSE value comparison without and with dropout layer implementation for driver and passenger obtained in training the model are presented in Table 2 shows after being trained.

Table 2
RMSE value comparison without and with dropout layer implementation for driver and passenger's model

No. of hidden nodes	Driver		Passenger	
	RMSE value without dropout layer	RMSE value with dropout layer	RMSE value without dropout layer	RMSE value with dropout layer
1	1.8995	1.9082	3.3148	3.3194
2	1.8599	1.8803	3.3529	3.3521
3	1.8387	1.8762	3.3762	3.2855
4	1.8902	1.8630	3.3379	3.3411
5	1.8556	1.8567	3.3931	3.3469
6	1.8607	1.8659	3.3481	3.3402
7	1.8579	1.8731	3.3414	3.3411
8	1.8633	1.8687	3.3614	3.3367
9	1.8663	1.8587	3.3613	3.3645
10	1.8633	1.8668	3.3733	3.3510
11	1.8761	1.8614	3.3768	3.3752
12	1.8653	1.8647	3.3689	3.3704
13	1.8560	1.8532	3.3845	3.3635
14	1.8956	1.8602	3.3718	3.3869
15	1.8430	1.8556	3.3798	3.3913
16	1.8349	1.8718	3.3899	3.3916
17	1.8473	1.8875	3.3800	3.3729
18	1.8816	1.8599	3.3828	3.3817
19	1.8520	1.8688	3.3764	3.3697
20	1.8547	1.8630	3.3645	3.3798

Figure 5 and 6 show the RMSE values of the driver's model that are presented graphically without the dropout layer and with dropout layer implementation respectively.

Fig. 5. Driver's RMSE value without dropout layer

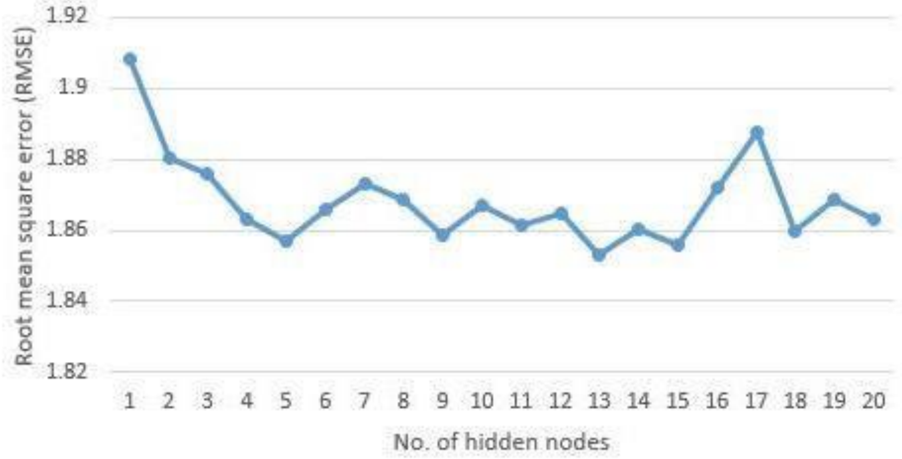

Fig. 6. Driver's RMSE value with dropout layer

Figure 7 and 8 presented the RMSE values of the passenger's model graphically without the dropout layer and with dropout layer implementation respectively.

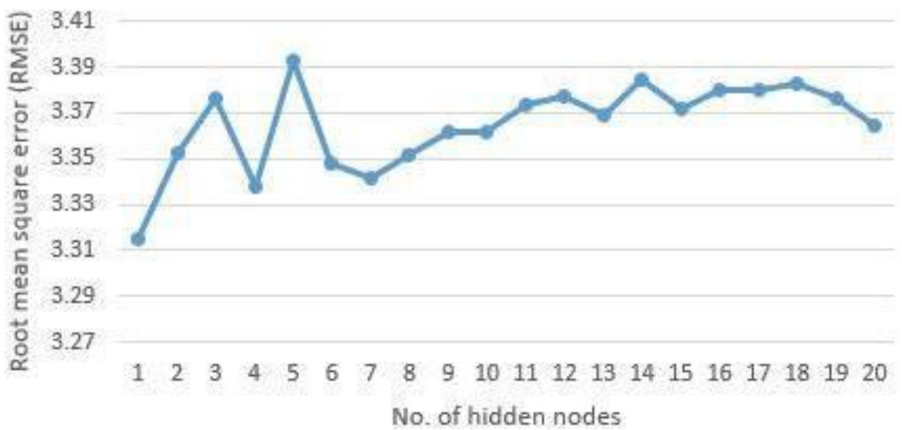

Fig. 7. Passenger's RMSE value without dropout layer

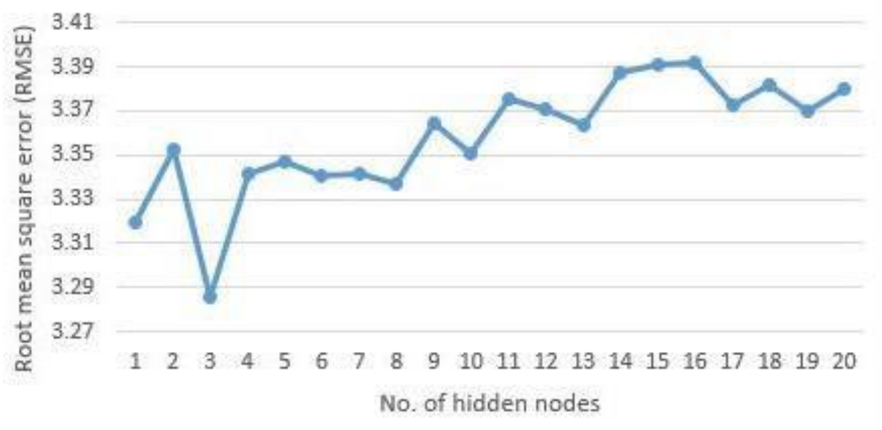

Fig. 8. Passenger's RMSE value with dropout layer

The results obtained from model training shows that the RMSE values for passenger's model is always higher than the RMSE values of driver's model. On average, the RMSE value of driver's model for both with and without dropout layer are 1.863095 and 1.868185 respectively while for passenger's are 3.36679 and 3.358075 respectively. The lowest RMSE value for passenger model is at the implementation of 3 and 1 number of hidden neurons for the dropout layer implemented model and without dropout layer. As for the driver case, the lowest RMSE value generated at the number of hidden neurons of 16 and 13 for model without and with dropout layer respectively.

Table 3
Lowest RMSE value comparison without and with dropout layer implementation for driver and passenger

Category	RMSE value without dropout layer	RMSE value with dropout layer	Difference in RMSE value between without and with dropout layer implementation	Percentage difference (%)
Passenger	3.3148	3.2855	0.0293	0.88
Driver	1.8349	1.8532	0.0183	1.00

The lowest RMSE value of the NN model of the driver is 1.8349 which is at 16 numbers of hidden neuron and 1.8532 which achieved by 13 number of hidden neurons with and without dropout layer implementation respectively produced a difference of 0.0183 in which equivalent to 1.00 %. For the passenger's NN model, the lowest RMSE value is produced at 1 number of hidden neurons with the value of 3.3148 without the dropout layer and at 3 numbers of hidden neuron with RMSE value of 3.2855 for the model that applied dropout layer in modelling. The difference between both models is 0.0293 which carry 0.88 % difference in values.

The regression results of the trained model are presented in Table 4 in shows that the regression value of the driver's trained model is always higher compared to passengers with the average value of 0.963188 and 0.9629005 for driver's model without and with the usage of dropout layer respectively that contributed to 0.05 % difference. As for the passenger's model, the value of regression is 0.896536 and 0.896571 for the model without and with the usage of dropout layer respectively with difference of 0.08 %.

Table 4
Regression value comparison without and with dropout layer implementation for driver and passenger's model

No. of hidden nodes	Driver		Passenger	
	Regression value without dropout layer	Regression value with dropout layer	Regression value without dropout layer	Regression value with dropout layer
1	0.96151	0.96100	0.89907	0.89917
2	0.96258	0.96287	0.89815	0.89812
3	0.96395	0.96243	0.89695	0.89834
4	0.96250	0.96336	0.89765	0.89783
5	0.96359	0.96346	0.89706	0.89701
6	0.96420	0.96300	0.89732	0.89693
7	0.96368	0.96329	0.89673	0.89717
8	0.96308	0.96334	0.89609	0.89638
9	0.96334	0.96371	0.89704	0.89632
10	0.96288	0.96311	0.89636	0.89664
11	0.96281	0.96316	0.89586	0.89602
12	0.96350	0.96297	0.89587	0.89626
13	0.96383	0.96353	0.89591	0.89609
14	0.96170	0.96256	0.89597	0.89530
15	0.96434	0.96345	0.89564	0.89512
16	0.96399	0.96289	0.89579	0.89550
17	0.96358	0.96161	0.89577	0.89596
18	0.96178	0.96253	0.89556	0.89555
19	0.96350	0.96291	0.89574	0.89622
20	0.96342	0.96283	0.89619	0.89549

Table 5
Regression value at the lowest RMSE value comparison without and with dropout layer implementation for driver and passenger

Category	Regression value without dropout layer at lowest RMSE value	Regression value with dropout layer at lowest RMSE value	Difference in regression values at lowest RMSE without and with dropout layer implementation	Percentage difference (%)
Passenger	0.89907	0.89834	0.00073	0.08
Driver	0.96399	0.96353	0.00046	0.05

Figure 9 and 10 shows the comparisons of the head tilting angle response to the vehicle lateral acceleration for the unlearned data, estimated data without and with the application of the dropout layer in the model for the lowest RMSE value of driver's and passenger's model respectively.

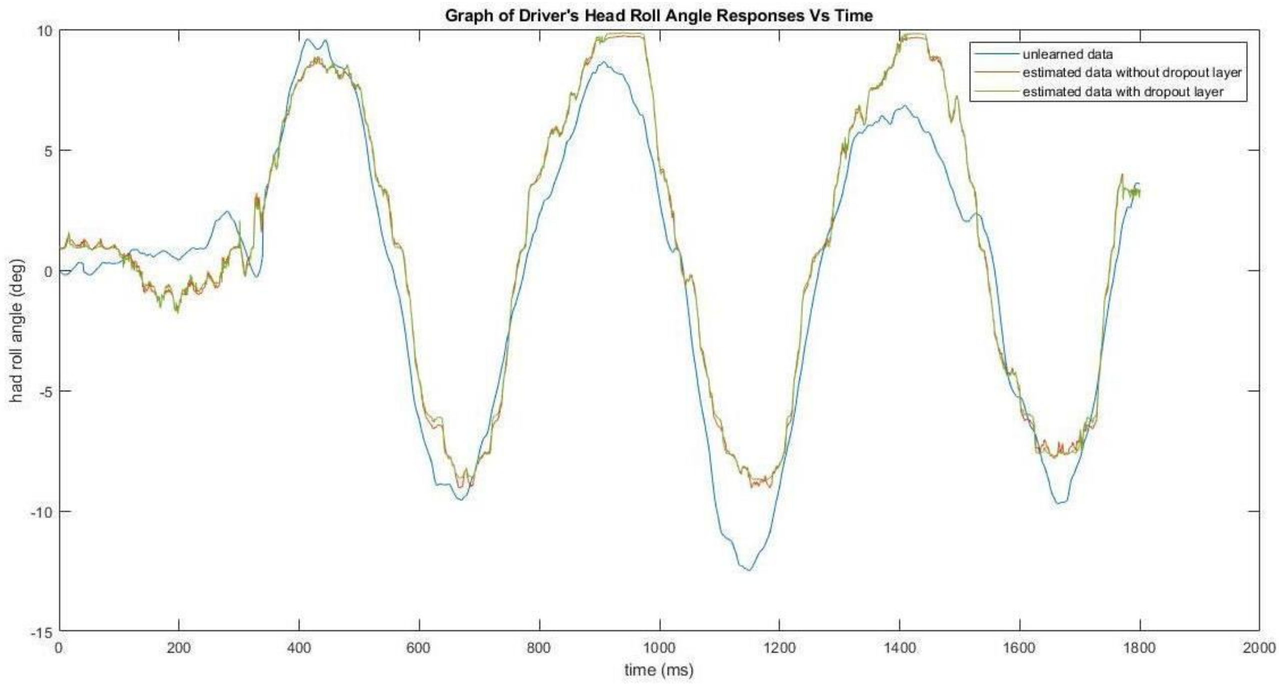

Fig. 9. Driver's head roll angle response comparison

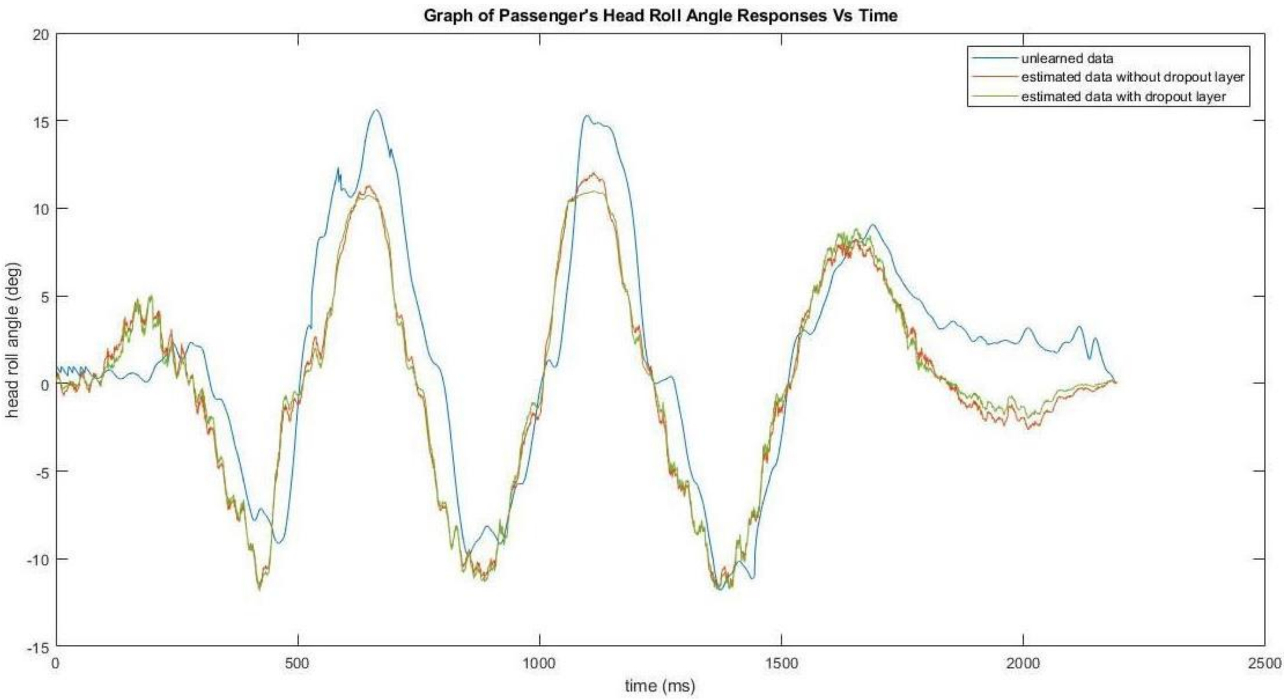

Fig. 10. Passenger's head roll angle response comparison

For Figure 9 and 10, the blue-lined graph represents the response of unlearned data to the vehicle lateral acceleration while the red-lined and green-lined graph are the output produced by the model without and with the implementation of dropout layer for the model that produced the lowest RMSE value. The graph of unlearned data is slightly different from the estimated output produced. Nevertheless, the difference is clearly visible for both driver and passenger's case. However, the estimated response with and without the dropout layer usage did not show noticeable difference in Figure 9 and 10 as the results shows only slight difference graphically.

The best number of hidden neurons for driver is 16 for model without dropout layer and 13 with dropout layer while 1 and 3 for the passenger's model without and with dropout layer respectively. The best number of hidden neurons in the model are different from the previous research conducted by Saruchi *et al.,* [4] in which the best number of hidden nodes is 17 for the driver's model and 8 for passenger's model. This could happen due to the difference in parameters used in both of the experiments such as the type of activation function, alpha values or training algorithms that being set in the experiments that are not being stated as constant variable that lead to the training of the model without dropout layer being conducted in this work in order to make sure that the variables used in experimenting the model without and with dropout layer are kept constant. However, based on the result obtained, it could be concluded that the best model for the head tilting angle prediction of the driver always have higher number of hidden neurons compared to the passenger's prediction model in both experiments conducted. This also applies to the model with dropout layer.

Based on this work, it is proven that the implementation of dropout layer in a non-complex NN model did not produce a significant difference in terms of model accuracy improvement. This is proven by the difference in terms of value in the lowest RMSE values produced during the model testing using the generalized data. The RMSE value for the passenger's head tilting angle prediction model are lower when the dropout layer is implemented in which shows that the estimated output did not deviate far from the actual output by 0.08 %. However, in the driver's head tilting angle prediction model, it did not show improvement as the RMSE value increase by 1.00 % with the implementation of dropout layer. Hence, no significant difference could be analyzed from the output produced. in this experiment proving that the implementation of dropout layer in non-complex NN model that use the number of hidden neurons that varies between 1 to 20 that made up a single hidden layer did not necessarily improve the model accuracy.

However, the regression value for both in driver and passenger case slightly decreased with the implementation of dropout layer in designing the model by 0.05 % and 0.08 % respectively. This shows that the although the implementation of dropout layer are not proven to improve the accuracy output value produced in this experiment, it could reduce the overfitting issue. This is due to the nature of the regression in which when the value reached 1, the value over fit the graph. This issue is known as overfitting. Reduced regression value could reduce the fitting of the data in which provides the model with better generalization to the variation of inputs presented.

4. Conclusion

To conclude, through this work, a prediction model for head tilting angle of car occupants are able to be designed using machine learning and the prediction model performance in terms of accuracy and fitting with respect to the implementation of dropout layer in hidden layer are able to be analysed. This work successfully proves that the implementation of dropout layer able to reduce overfitting in the head tilting angle prediction model in regression model of the non-complex ANN architecture. Hence, dropout layer implementation is not limited to complex ANN model and Convolutional Neural Network (CNN).

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