

Emotion and Attention of Neuromarketing Using Wavelet and Recurrent Neural Networks

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Abstract— One method concerning evaluating video ads is neuromarketing. This information comes from the viewer's mind, thus minimizing subjectivity. Besides, neuromarketing can overcome the difficulties of respondents who sometimes do not know the response to the video ads they watch. Neuromarketing involves information from what customers think is captured by an Electroencephalogram (EEG) device. Meanwhile, if the electrical signal information in the brain is corresponding to an understanding of one's psychology, it is called neuropsychology. This field consists of emotions, attention, and concentration variables. This research offered neuromarketing base on emotion and attention of EEG signal using Wavelet extraction and Recurrent Neural Networks. Measurement of EEG variable every two seconds while watching video ads. The results showed that Wavelet and Recurrent Neural Networks could provide training data accuracy of 100% and 89.73% for new data. The experiment also gave that the RMSprop optimization model for the weight correction contributed to higher correctness of 1.34% than the Adam model. Meanwhile, using Wavelet for extraction can increase accuracy by 5%.

Keywords— Neuromarketing, emotion, attention, EEG signal, video ads, recurrent neural networks, wavelet

I. INTRODUCTION

In attracting someone's interest in a product or service offered, marketing teams usually promote the product or service, one of which is in the form of video advertisements. The cost of filtering advertisements is costly, so it is necessary to evaluate it first, which directs viewers to buy it. Video ads need to be tested for the effectiveness of video advertising so that the message conveyed can be well communicated and can attract the attention and emotions of potential customers.

Standard evaluation of video ads uses interviews and questionnaires. However, the drawbacks, these two methods tend to be subjective and sometimes inconsistent. Sometimes the respondent does not know the accurate perception of the video ad that he watched. Besides, the assessment is difficult to do in real-time for each video scene.

Today, marketing can take advantage of using the information on electrical activity in the brain, called Neuropsychology. This method can help improve the possibility of marketing research to increase efficient trade-off. This breakthrough overcoming people cannot fully articulate their preferences of a product or advertisement [1].

Neuro-marketing is an emerging interdisciplinary field, situated at the borderline between neuroscience, psychology, and marketing [2]. This method, based on neuropsychology provides a real competitive advantage in an increasingly saturated market [3]. Conventional evaluation of video ads is by interview or survey. However, both methods are less measurable and tend to be subjective and inconsistent. Thus,

the field of Neuro-marketing is the focus of attention of many studies.

Neuropsychology is the study of the relationship between electrical activity in the brain and behavior in humans. Neuropsychologists have several variables, including emotions, attention, and concentration. One of its implementations is the response of one person's interest to a particular video ad, as it can be used as a tool to test the effectiveness of that video [4].

Emotion is a feeling that appears after stimulation from inside and outside the body. It influences behavior both consciously and unconsciously. In marketing needs to consider emotional measurement. Previous studies measured positive emotions and negative emotions that impact on loyalty intentions. Positive emotions are happy, happy, and enthusiastic, while those that include negative emotions are angry, disappointed, and hesitant [5] The introduction of sensations is also used to find out the customer's emotional reactions to different types of images [6].

Attention is an interest or interest of someone in an object, person, or situation that has relevance to the object or person. The attention response in watching advertisements is not only influenced by the scenario, visual, sound of the video, but sometimes it is influenced by the product brand. Therefore, neuro-marketing analysis usually uses the attention variable using video ads from the same brand [4].

EEG signals have been used in the classification of emotions using Wavelet and SVM as stimulation of music videos [7]. Other studies sought the relationship between EEG signals and feelings with a linear dynamic system approach [8]. Usually, the identification of emotions is captured of temporal channels T7 and T8 compared to other channel information [9]. In classifying EEG signals, several approach techniques related to feature extraction such as time-domain analysis, frequency domain analysis, time-frequency domain analysis [10]. Other research also used EEG signals in detecting consumers' latent emotions when watching commercial TV [11].

Deep Learning is part of machine learning, which can improve the way computers learn to be able to resemble the capabilities of the human brain through deep learning. One of the Deep Learning methods that can be used for time-series data is Recurrent Neural Network (RNN). RNN is usually appropriate for sequential data connected. There are several units in the RNN, one of which is Long-Short Term Memory (LSTM). LSTM functions to overcome long-term memory dependency, which informs between neurons in the RNN architecture. However, time-series data processing, such as EEG signals can be done using one-dimensional Convolutional Neural Networks (CNN). 1D CNN has been

used to analyze epileptiform spikes on EEG signals [12], then classify emotions accurately [13] [14].

Previous research also combined CNN and LSTM. CNN was used to connect correlations between adjacent channels by converting EEG sequential data into 2D frame sequences and LSTM to process contextual information [15].

This research proposed a method for identifying emotional responses and attention against advertising videos using Wavelet extraction and RNN. The two variables are emotion (happy, sad, surprised, and flat or neutral) and attention that has two classes of "attention" and "not attention" so that the total becomes eight classes. The model was performed on EEG signals every two seconds according to one ad video scene.

II. RELATED WORKS

A. Neuromarketing

Neuromarketing consists of emotion, attention, and concentration. Usually, the emotional response toward video ads, influenced by the visual effects of the video, such as images, colors, text, and others related to visualization [16]. While the level of attention appears tends to emerge when stimulated by a brand or brand advertised.

Previous research related to neuropsychology or neuromarketing captured emotional response against advertising video stimulation. Emotion identification throughout EEG signals that proceed by Fast Fourier Transform and Levenberg-Marquardt Backpropagation and has an accuracy of 77.67% on test data and 100% of training data [17]. Other research identified attention level after watching ads video. It has three classes particularly interested, less interested, and not interested with 71% of accuracy [4].

Identification of emotional variables and attention can be achieved using an Electroencephalogram (EEG). EEG devices record electrical activity in the brain. EEG signal characteristics can be divided into frequency components, and are called Delta waves (0.5-3 Hz), Theta (4-7 Hz), Alpha (8-13 Hz), Beta (14-30 Hz), and Gamma 30- 60 Hz).

Therefore, the extraction of EEG signals into a frequency component becomes useful, including for neuropsychology. One method commonly used to extract non-stationary signals such as EEG signals is Wavelet transformation.

B. Wavelet Extraction

In signal processing, feature extraction is needed to eliminate noise and retrieve the necessary features to be used as input at the identification stage. One method that is useful for frequency extraction is Wavelet. The process can extract signals based on the frequency range to obtain Alpha, Beta, Theta, and Gamma waves.

This Wavelet Transformation functions to separate each wave frequency at the signal taking the required signal frequency. There are two processes in Wavelet transformation, namely decomposition, to perform signal extraction and conduct reconstruction to restore the signal. The fundamental Wavelet function can be seen in (1).

$$\psi_{\sigma,\tau}(n) = \frac{1}{\sqrt{|\sigma|}} \psi\left(\frac{n-\tau}{\sigma}\right) \quad (1)$$

Where σ is a scale variable and τ is a signal shift.

Decomposition in Wavelets is done using (2) for approximation or a low-pass filter and (3) for detail or high-pass filter.

$$y_{low}[k] = \sum_n x[n] * g[2n - k] \quad (2)$$

$$y_{high}[k] = \sum_n x[n]. h[2n - k] \quad (3)$$

Where $[n]$ is the original signal, $g[n]$ is the low-pass filter coefficient, $h[n]$ is the coefficient of the high-pass filter, k , n is the 1st index to the length of the original signal.

There are several functions to obtain coefficients for feature extraction in Wavelet. One of them is Daubechies 4, which was used in previous studies for emotional identification [18], epilepsy [19].

C. Recurrent Neural Networks

RNN is part of a neural network with a repetitive architecture of Backpropagation learning algorithms. Processing processes call time-series data repeatedly to make the input process so that it is suitable for the connected data.

RNN has the disadvantage of short-term memory, so has several variations of the gate. There are several units on the RNN to regulate the connections, including Gated Recurrent Units (GRU), Long-Short Term Memory (LSTM) and Backpropagation Through Time (BPTT) [20].

LSTM is units of the RNN. LSTM, which consists of an input gate, the output gate, and forget the gate. In the cell, it will remember values during a changing period. Long sequential data training is complicated to do by ordinary RNN models, such as Backpropagation through time (BPTT), which causes vanishing gradient problems [21].

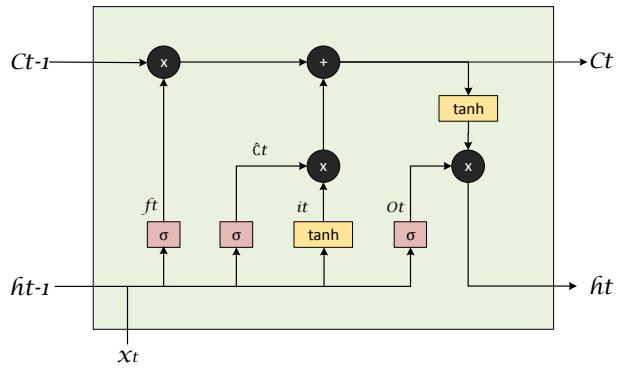


Fig. 1. LSTM cell architecture

Input neurons associated with hidden layer neurons and in the hidden layer, there is a cell that has three gates, as shown in Fig. 1. Input data is calculated using (4) using the ReLU activation function to change the negative vector value.

$$ReLU(x) = \max(0, x) \quad (4)$$

The value that has been changed to positive will be processed than to calculate the forget gate, which will decide which information will be discarded from the cell state [22]. The forget gate calculation uses (5).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (5)$$

Then through layer 2, the dropout layer where this layer will decide which information will be processed and which will not. This method is to minimize the number of neurons with a probability of 0.2. Next is to calculate the input gate wherein it will decide which value will be updated, as shown in (6).

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (6)$$

Where the input weight (W_i) multiplied by the previous hidden layer's weight range (h_{t-1}) with the input (x_t) added with bias. Meanwhile, the function of the cell decides the value of the vector that renew the value using (7).

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (7)$$

Then at (8) the value in the cell state will be calculated to update the value.

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (8)$$

Where (f_t) is the forget gate, (C_t) is the cell state, (i_t) is the gate input, and (\hat{C}_t) is the candidate cell to be updated in value.

The last is the dense layer, which will be the final output, can be seen at (9) and (10).

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (9)$$

$$h_t = o_t * \tanh(C_t) \quad (10)$$

Where σ is the sigmoid activation function, \tanh is the tangent activation function. W_f is the forget gate weight. W_i is the input weight, W_c is the cell state weight. W_o is the output weight of h_{t-1} cell state value in the previously hidden layer. Then, b_f is biased forget gate, b_i is an input bias, b_c is a cell state bias, b_o is an output bias, and x_t is the input vector value [21].

Previous studies used RNN for emotional identification [21], classification of motors imagery [23], and neuropsychological identification [24]. While the RNN model achieved an accuracy of 100%, and the MLPNN model reached 98.93% for the identification of epilepsy [25].

III. METHODS

A. Data Acquisition

Previous research recorded brain activity against visual advertising using a sampling rate of 256 per second on each channel with a duration of 2 seconds segmentation, which produced 512 data points [26].

In this study, the acquisition of EEG signals used 30 subjects. Each subject watched 20 ads videos like Table I.

The list of ads Video consists of 10 food products with different brands and ten different types of products and brands that were not the same. All video ads are taken from the Youtube site. Video advertisements that can stimulate the interest of the audience need to pay attention to several elements of color, for example, red [27]. In stimulating emotions, pink is often associated with optimism and

happiness, while the orange color is one to excite sad emotions [28].

The duration of recording time adjusts to the period of the video of the ad from 60 to 180 seconds. The recording was at varying times, particularly morning at 08:00, afternoon at noon and afternoon at 17:00 to minimize the influence of time. The recording keeps minimal environment noise to avoid disturbance during data acquisition.

The volunteers are 20-23 years and in healthy condition. In one recording of 30 narrators, 20 stimuli were given to produce 600 data sets. If it is repeated three times, it provides 1,800 data sets.

The recording is four channels EEG, particularly AF3, AF4, T7, and T8 when watching video ads. Before recording, subjects are allowed to condition to sit comfortably and relax before being given video ad impressions. Every time a video is finished, the next advertisement is with a 3-5 minute pause. After completing the march, the subject will be given a questionnaire about the video advertisement that has been shown to support knowing the emotions.

TABLE I. LIST OF ADS VIDEOS

| No | Title (in Indonesian) | Brand | Duration |
|----|---|-------------|----------|
| 1 | TVC Indomie - Air & minyak 60s | Indomie | 01:00 |
| 2 | Indomie - 45th Anniversary | Indomie | 01:00 |
| 3 | Drama Korea Soto Lamongan | Indomie | 01:30 |
| 4 | Bollywood Indomie Rasa Soto Padang | Indomie | 01:30 |
| 5 | Indofood Satukan Tekad dan Semangat Indonesia (60") | Indomie | 01:00 |
| 6 | #AyamSpicyMcD I Spicy Story Ending 1 | McDonald's | 01:00 |
| 7 | #AyamSpicyMcD I Spicy Story Ending 2 | McDonald's | 01:00 |
| 8 | #AyamSpicyMcD I Spicy Story Ending 3 | McDonald's | 01:00 |
| 9 | Rayakan Harapan Baru | McDonald's | 01:00 |
| 10 | Perjuangan Anak Bangsa Bersama McDonald's | McDonald's | 01:30 |
| 11 | Warna Kebahagiaan - Tulusnya Cinta | Ramayana | 03:00 |
| 12 | #ringanbersama - My Son, My Sun | BNI Syariah | 03:00 |
| 13 | Jadikan Ramadan Kesempatan Terbaik | Tokopedia | 02:00 |
| 14 | Iklan Ramayana Ramadan 2017: Bahagianya adalah Bahagiku | Ramayana | 03:00 |
| 15 | Bahagia Itu Kita yang buat | Bibli.com | 01:00 |
| 16 | GS Battery | GS Astra | 01:00 |
| 17 | Ramayana Horror Series - Benerin Dulu | Ramayana | 01:00 |
| 18 | Surprise | AT&T | 01:30 |
| 19 | Spotify Horror | Spotify | 01:00 |
| 20 | Komix Herbal | Komix | 01:00 |

EEG signals have complex shapes like Fig. 2, so signal extraction is only an important component that helps with classification problems.

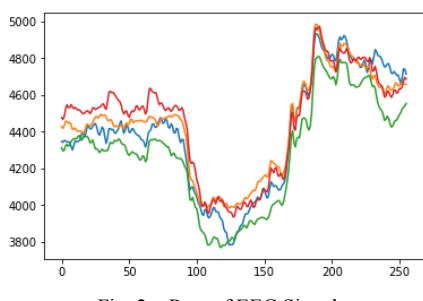


Fig. 2. Raw of EEG Signal

B. Design of Neuropsychological Identification System

Identification through several stages, namely pre-processing of segmented EEG signals before extracting using Wavelet. The last step of identification uses RNN with LSTM layer 1, dropout layer, LSTM layer 2, and dense layer like Fig. 3.

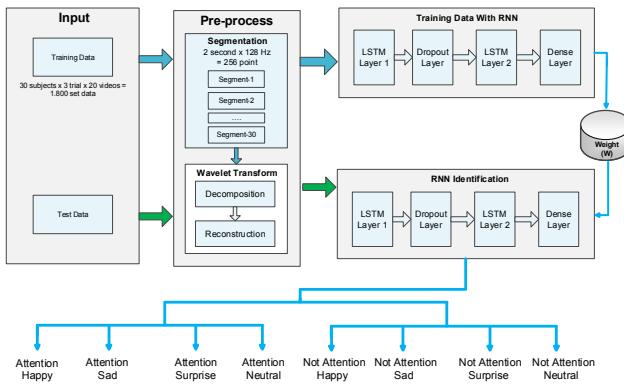


Fig. 3. Neuropsychology identification model

1) Segmentation

From the EEG signal during the duration of the video of the ad, the EEG signal proceeded in 60 seconds, which is divided every two seconds so produce 30 segments. If each section is two seconds with a 128 Hz sampling frequency, then 128 Hz x 2 seconds or 256 points are obtained. After that, the data normalization is carried out first in the range of values 0-1 before extracting using Wavelet.

2) Wavelet Transform

EEG signals that have a 128 Hz sampling frequency are decomposed using (2) and (3) as many as six steps as in Fig. 4 so that Alpha, Beta, Theta, and Gamma waves are obtained.

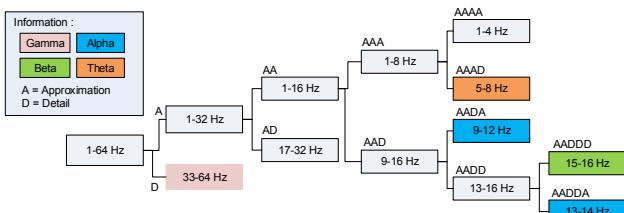


Fig. 4. Decomposition using Wavelet multilevel

This study used the Symlet2 wavelet function. The coefficient on the Symlet2 function has four coefficients on the approximation and detail that can be seen in (4) for the approximation coefficient and (5) for the coefficient of detail.

$$g_0 = \frac{1-\sqrt{3}}{4\sqrt{2}}, g_1 = -\frac{3-\sqrt{3}}{4\sqrt{2}}, g_2 = \frac{3+\sqrt{3}}{4\sqrt{2}}, g_3 = \frac{1+\sqrt{3}}{4\sqrt{2}} \quad (4)$$

$$h_0 = -\frac{1+\sqrt{3}}{4\sqrt{2}}, h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}, h_2 = -\frac{3-\sqrt{3}}{4\sqrt{2}}, h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}} \quad (5)$$

From (5), g_n is an approximation or a low-pass filter, and h_n is the high-pass filter.

Wavelet extraction produces 24 data from Alpha waves, 16 data from Theta waves, 8 data from Beta waves, and 128 data from Gamma waves. Therefore, the descent becomes 176 data on one channel, 704 points from four channels. EEG signals resulting from Wavelet extraction can be seen in Fig. 5

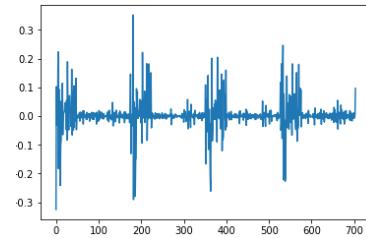


Fig. 5. Result of EEG Signal from Wavelet Extraction

3) Recurrent Neural Networks

At this stage, the RNN will receive the output of Wavelet extraction at the pre-processing step, which will be the input of the neuron for identification. Wavelet extraction has taken features from each of the Alpha, Theta, Beta, and Gamma waves. The feature vector as RNN input can be seen in Table II.

TABLE II. FEATURE VECTOR

| No | Feature vector | Data Point Length (One Channel) | Data Point Length (4 Channels) |
|----|----------------|------------------------------------|-----------------------------------|
| 1 | Theta Wave | 16 | 64 |
| 2 | Alpha Wave | 24 | 96 |
| 3 | Beta Wave | 8 | 32 |
| 4 | Gamma Wave | 128 | 512 |
| | Total | | 704 |

Features as many as $x_1 - x_{704}$ or 704 data points from the four extracted channels will be input neurons on RNN. System configuration used to conduct RNN training and classification, as in Table III.

TABLE III. SYSTEM CONFIGURATION OF RNN MODEL

| Model | Neuron Size/ Dropout Probability |
|---------------------|-------------------------------------|
| lstm_1 (LSTM) | 704 |
| dropout_1 (Dropout) | 0.2 |
| lstm_2 (LSTM) | 64 |
| dense_1 (Dense) | 8 |

There are four layers, namely LSTM layer 1, with a total of 704 neurons following the input neurons resulting from feature extraction. The dropout layer has a probability of 0.2. Then, LSTM layer 2 has 64 neurons as a result of the layer dropout. The last stage is the dense layer, which becomes the output vector, which has eight neurons from 8 classes.

IV. RESULT AND DISCUSSION

In this study, there are two optimization models for correction of weights, namely Adaptive Moment Estimation (Adam) and RMSprop. Both models were tested to get the best accuracy. The experiment also compared the accuracy of models using Wavelet extraction and did not use Wavelet.

The RNN configuration uses a batch size of 40, with 150 epochs in each test performed. From all data sets, 80% were used for training data and 20% for validation data (non-training data). The Adam optimization model is adaptive learning, which is learning with dynamic parameters, thus providing correctness, as shown in Fig. 6.

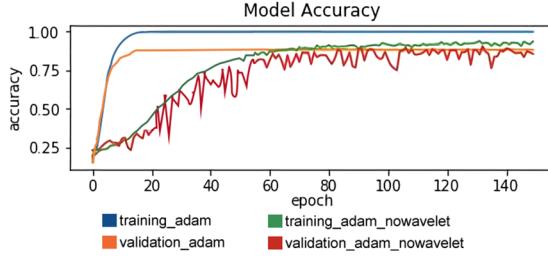


Fig. 6. Accuracy of the Adam model

The accuracy obtained using Adam with Wavelet extraction of 100% for training data, and 88.3% for testing data. The training was accomplished before, which needed 352.08 seconds. Meanwhile, the Adam model without Wavelet, the accuracy achieved was only 96.9% of training data and 87.5% of validation data by taking training time for 610.38 seconds. Adam's optimization model with Wavelet, the accuracy of validation data continued to rise from epoch 1 to 10 until convergence reaches 88.3% accuracy in iteration 11-150. Meanwhile, the Adam optimization model without Wavelet results in the accuracy of fluctuating upward validation data reaching convergent values at the 20th epoch to an accuracy of 87.5%. This result is consistent with the graph of the losses value from the Adam optimization model, as can be seen in Fig. 7.

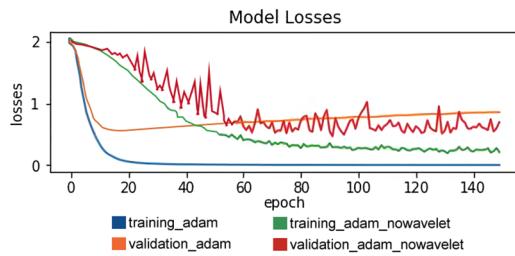


Fig. 7. Losses of Adam model

The loss value from the Adam optimization model with Wavelet is 0.8587. Although it is quite stable, it is not nearly convergent. Whereas for the losses value of Adam without Wavelet model is 0.6150 with fluctuating graphs and not yet converging after 140 epoch.

Root Mean Square prop Optimization (RMSprop) is a learning method that limits vertical oscillations during learning so that it can increase learning speed. The algorithm can take more significant steps in the horizontal direction when doing training that will make converging faster. The RMSprop model is a development of the Adagard model for being able to overcome the problem of decreased learning levels. RMSprop optimization is very similar to the Garient

descent algorithm with momentum — the difference between both methods of how the gradient is calculated. The main idea of RMSprop is to maintain the average movement of the squared gradient for each weight. This reason makes the method has better accuracy and converges quickly.

For models using RMSprop optimization, the graph shows that RMSprop using the Wavelet method accuracy obtained 1% higher in the test data compared to Adam optimization using Wavelet. Charts of losses and correctness as in Fig. 8.

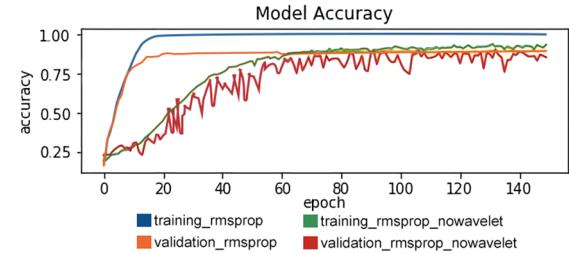


Fig. 8. Accuracy of RMSprop model

The RMSprop optimization model with Wavelet provides 100% accuracy of training data and fluctuating accuracy from validation data to 54th epoch to converge on 89.7% accuracy with learning during 130.68 seconds. Meanwhile, the RMSprop without Wavelet optimization model provides an accuracy of 93.6% of training data and 85.7% of unstable (fluctuating) validation data with learning during 174.72 seconds. The loss value of the RMSprop optimization model can be seen in Fig. 9.

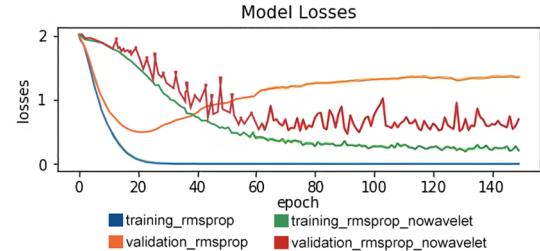


Fig. 9. Losses of RMSprop model

The value of RMSprop losses with Wavelet is 1.3514 for validation data with graphs that are not nearly convergent. Likewise, the RMSprop model without Wavelet losses is 0.6960 and shows that the value is not roughly convergence, and the chart is fluctuating. Comparison of the amount of accuracy and Losses on Adam and RMSprop optimization asTable IV.

TABLE IV. COMPARISON OF LOSS AND ACCURACY USING ADAM AND RMSPROP

| Experiment | Train Data | | New Data | |
|------------------|------------|----------------|----------|--------|
| | Accuracy | Loss | Accuracy | Loss |
| Adam | 96.96 | 0.1164 | 87.50 | 0.6150 |
| Adam+ Wavelet | 100.0 | 0.0031 | 88.39 | 0.8587 |
| RMSprop | 93.67 | 0.2113 | 85.71 | 0.6960 |
| RMSprop+ Wavelet | 100.0 | 0.0000 0.29 | 89.73 | 1.3514 |

The experimental results show that the use of Wavelet transformations for EEG signal extraction provides higher and

more stable accuracy during training. This result is consistent with the characteristics of non-stationary EEG signals, minimized by Wavelet.

V. CONCLUSION

Emotions and attention of Neuro-marketing through EEG signals can help evaluate ad videos in real-time for each scene. Attention level increased when the logo image or text name of the brand appear either at the beginning, in the middle, or at the end of the ad video clip.

In meanwhile, the emotions appeared while watching video ads. Happy emotion match by comedy video ads. Sad emotions increase by heartbreaking scenes. Surprise emotions appear on ads video that contains shocking scenes. Tense feelings emerge from video ads that are a bit of horror, while neutral emotions appear from the video advertisements in which there are many texts. Besides jingle (background) is a supporting element of an advertising video that significantly influenced the appearance of one's emotions.

Emotions and attention of Neuro-marketing resulted in 100% accuracy of training data and 89.73% of validation data. The RMSprop optimization model is more stable and improved the Adam model in terms of accuracy. Meanwhile, the use of Wavelet extraction can increase the correctness up to 4% by minimizing the non-stationary nature of the EEG signal.

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