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Modeling of Videos Emotion Recognition System using Recurrent Neural Networks

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Abstract: With the significant rise in the online and digital YouTube video libraries, internet speed, handheld devices with applications to play and organize video libraries and stress management therapies provided by doctors for treatment of various diseases, demand for organizing video libraries has also been increased. Videos and emotion are strongly related to each other. Emotion can be felt by everyone by watching these videos. In this paper, video emotion recognition (VER) system is proposed by using Long Short-Term Memory networks. Long Short-Term Memory networks possess long short-term memory due to which relevant data can be passed through long distance and predictions can be made according the stored relevant data. Two VER system systems are modelled to classify the videos in four and eight classes of emotion. Three observations are carried out for both the systems in order test the model by considering 40, 80 and 120 hidden layers. The accuracy and loss are analysed for all the three observations conducted. The accuracy for third observation reaches 94.97% for system 1 and 92.8% for system 2. Results also reveal that the loss is decreased to 0.021 for system 1 and 0.133 for system.

Keywords: Video Emotion Recognition (VER), Long Short-Term Memory (LSTM) networks, Recurrent Neural Network (RNN).

1. INTRODUCTION

The VER system is designed to manage large video files that can be viewed, searched and otherwise queried. The VER system, developed using different machines learning techniques, is used to evaluate the perception of video clips, the system consists of five simple steps: data collection, preprocessing, annotation, feature analysis and classification. Consider conducting research using a large database covering all video types available in different formats, including ensuring the data is not affected by album effects or performance effects [1]. Various model datasets are also available online, such as IEMOCAP: Interactive Emotional Binary Action Capture Database [2], MELD: Multimodal Multipartite Dataset for Emotion Recognition in Conversations [3], and the CMU-MOSEI dataset and interpretation of existing Dynamic fusion graphs [4]. Video data was converted to a clear sample format such as sample frequency (44100 Hz) for fair evaluation. The views expressed by the video do not remain constant over time. A complete sample video can withstand different emotions. Therefore, the most representative 40-50 second clips in the video are considered and used for cognitive purposes [5]. Conceptual models such as Russel [6], Thayer [7] and Plutchik [8] are used to classify movies into different categories. Features such as energy, sound, tone, volume and rhythm, which contain information about the video pieces, were revealed to represent the perceptual dimensions of the film. Audio features were extracted using various tools such as Psysound 3 [9], Marsyas [10], and MIR Toolbox [11]. Existing information on different groups with different characteristics is used to determine the relationship between emotions and videos while training process. Various machine learning algorithms used as classifiers include support vector machines (SVM) [12], [13], K-nearest neighbor (KNN) [14], [15] and artificial neural networks (ANN) [16], [17]. Although there are many machine learning algorithms, emotion recognition process still has limitations. For example, there is a lot of information available online in many languages, but the knowledge base is limited to certain video formats. In this paper, the VER system is modeled using short-term temporal (LSTM) networks. LSTM networks are a subclass of Recurrent Neural Networks (RNN) in which past data can be stored and new data can be predicted based on data stored in memory. Convolutional neural networks (CNN) take data from the image and transform the music into spectrograms to model VER systems [18], [19]. RNN uses the instruction sequence directly and is used for classifying text, audio, and speech [20], [21]. According to previous studies RNN is able to learn short sequence data. Sequence data is the data in which previous data is followed by data in succession. A temporary file is a file that contains sequential data that builds on previous data. In RNNs, information from previous steps may be lost when considering long-term sequences due to short-term memory problems [22], [23]. LSTM networks are capable of learning from sequential data over long periods of time. LSTM networks are less sensitive to time variation and are considered a better choice for data analysis than simple RNNs. LSTM networks have an internal structure that includes gates that help control the flow of data. This is how Gates can learn to determine the importance of data connections. These gates provide insight into which components in a segment are important to retain for further processing. By doing that, it can pass the related information down the long chain of sequences to create predictions and forget

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the non- related information. This paper contributes by classifying the videos on the basis of emotion in four and eight emotion classes by using LSTM network.

The following points are considered to model the VER system by using LSTM network.

a) VER system is proposed and modeled by using LSTM network for classification of videos based on emotions.

b) The proposed system is modeled by using Hindi dataset consisting of 1000 videos.

c) Three observations are carried out by using different number of hidden layers in order to classify the videos in four and eight classes of emotion Three observations are carried out to test the model by considering 40, 80 and 120 hidden layers.

d) The accuracy and loss are determined for all the three experiments conducted.

The LSTM network architecture used for modelling VER system is discussed in section 2 followed by description of system modelling in section 3. The performance of the modelled system is analysed in section 4. Section 5 provides the conclusion of the work carried out in this paper.

2. LSTM Network Architecture

The LSTM network consists of five layers as shown in fig. 1. The network layers are described in this section.

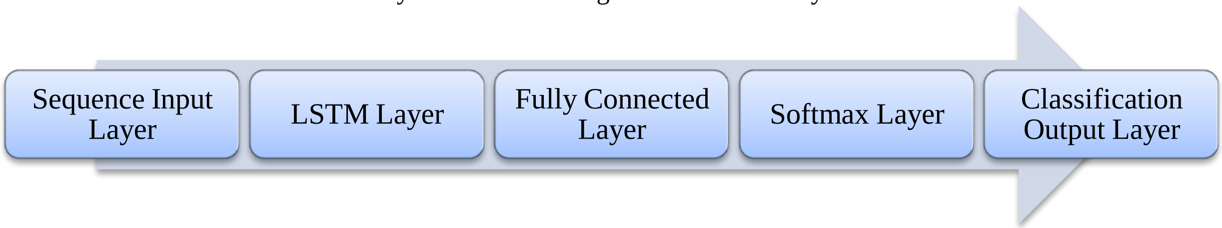

Fig 1 LSTM network architecture

2.1 Sequence Input

This layer is used to input the sequence data to the LSTM layer. Sequence data is the data in which previous data is followed by data in succession. Thus, the new can be predicted if the previous states information is stored. Sequence layer normalizes the data provided to it.

2.2 LSTM Layer

An LSTM layer can be used for long sequence data and can store the related information for longer time steps. LSTM layer consists of two states hidden state (output state) and cell state. The hidden state at any time t contains the output of LSTM layer for that time step. The information related to previous time steps is stored in cell state. For every time step the relevantinformation may be added to cell state and non - relevant information may be removed. LSTM layer contain gates which can be learned to detect the importance of data in sequence on the basis of which the information can be added or forget. The flow of data through LSTM layer at time t is shown in fig 2. The forget gate, cell state, input gate and output gate are represented in LSTM layer architecture[22], [24], [25].

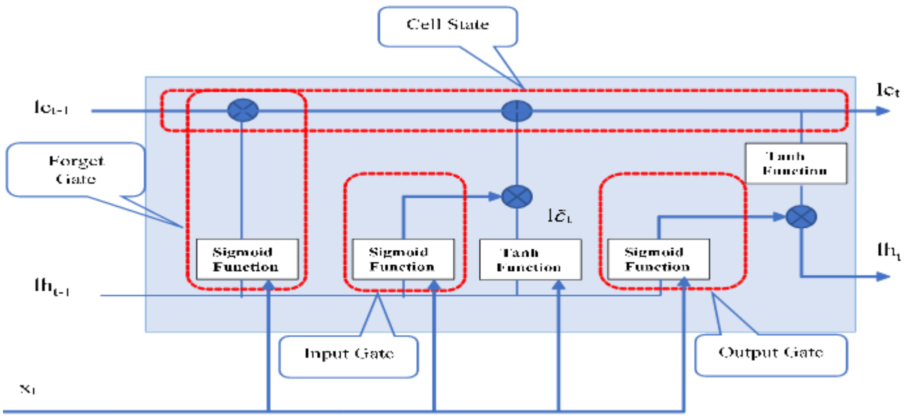

Fig 2 LSTM Layer

The operations used in LSTM layer architecture are used to help the layer to forget the non-relevant data, update the information and predict the output states. The tanh activation function helps to adjust the values between -1 and 1 and sigmoid activation function ensures that the value should lie between 0 and 1.

The learnable weights of an LSTM layer are input weights represented by vector W_{lstm}, recurrent weights represented by vector R_{lstm} and a bias represented by vector B_{lstm}. The matrices W_{lstm}, R_{lstm} and B_{lstm} are formed by concatenating the weights of gates used to form the LSTM layer as represented by equation 1.

$$W_{lstm} = [W_{li}\ W_{lf}\ W_{lc}\ W_{lo}] \quad R_{lstm} = [R_{li}\ R_{lf}\ R_{lc}\ R_{lo}] \quad B_{lstm} = [b_{li}\ b_{lf}\ b_{lc}\ b_{lo}] \qquad (1)$$

Where li represents the lstm input gate, forget gate of lstm is represents by lf, cell state for lstm is represented by lc and lstm output gate is represented by lo.

The cell state is represented by lc_t for time step t as shown in equation 2.

$$lc_t = lf_t \odot lc_{t-1} + li_t \odot l\tilde{c}_t \qquad (2)$$

Element wise vector multiplication is represented by $\odot$.

The hidden state at time step t is represented by lh_t as shown in equation 3.

$$lh_t = lo_t \odot \sigma_c(lc_t) \qquad (3)$$

σ_c represents the tanh activation function for the state.

2.3 Forget gate

The importance of information is determined by this gate. This gate decides which information is to be kept and which is to be forget for further processing. Information received from the previous output or hidden state and current state information is given to sigmoid function. The output of sigmoid function ranges between 0 and 1, where values towards 0 are to not important and can be ignored and values towards 1 are to be retained for further processing. The forget gate of lstm at time step t is described by equation 4.

$$lf_t = \sigma_g(W_{lf}x_t + R_{lf}\,lh_{t-1} + b_{lf}) \qquad (4)$$

2.4 Input Gate

This gate updates the cell state. The previous hidden state and current input are passed through the sigmoid function to decide the importance of information as in forget state. It decides which values will be updated by transforming the values between 0 and 1. 0 means not important, and 1 means important. Then the previous hidden state and current input is also passed through tanh function which helps to maintain the network and keeps the value of information between -1 and 1. Then the output of sigmoid and tanh function is multiplied and fed to cell state. The input gate at time step t is given by equation 5.

$$li_t = \sigma_g(W_{li}\,x_t + R_{li}\,lh_{t-1} + b_{li}) \qquad (5)$$

σ_g represents the gate activation function.

2.5 Cell State

The cell state is updated by the information received from the input gate and forget gate. The cell state is multiplied by the forget gate output. If the output of forget gate is zero then the values in cell state may be dropped. Then the result of multiplier is added to the input gate output to update the cell state to new related values and updated cell state is achieved. The cell state at time step t is given by equation 6.

$$lc_t = \sigma_c(W_{lc}\,x_t + Rl_c\,lh_{t-1} + bl_c) \qquad (6)$$

2.6 Output Gate

The next hidden state is controlled by output gate. The previous hidden state and current input are passed through sigmoid function and the updated cell state is passed through tanh function. The output of sigmoid function and tanh function are multiplied to determine the new hidden state or output state. The updated cell state and hidden state are further carried and used as inputs for the next time step. The output gate at time step t is given by equation 7.

$$lo_t = \sigma_g(W_{lo}\,x_t + R_{lo}\,lh_{t-1} + b_{lo}) \qquad (7)$$

σ_g represents the gate activation function.

2.7 Fully Connected Layer

Fully Connected Layer predicts the output of whole dataset for each class of emotion used for classification[18], [26]. After the processing of LSTM layer, the data is fed to fully connected layer that outputs a vector of m dimensions where m is equal to number of classes that the network is designed to predict. This vector contains the probabilities any signal for each class that is to be predicted by system.

2.8 Softmax Layer

Softmax Layer is considered as classification layer of the network[27]. The output layer makes use of softmax layer to produce the classified output. In softmax layer, the dimension of output equals to the number of emotion classes considered in the model. Each of the dimension belong to one particular emotion label.

2.9 Classification Output Layer

Classification output layer is used to carry the loss function used for training purpose, output size and labels for classes used for classification purpose[19], [26].

3. METHODOLOGY

The VER system is designed for classifying the Hindi videos in four and eight emotion classes. In this proposed work 1000 Hindi videos are collected from online sources. 30-second video clips are extracted from complete videos by considering most representative part of video in standard format of 44100 Hz sample rate and 16 bits precision. Further windowing and framing techniques are applied to 30- second clips. Windowing is directly in co-operated with the Fourier transform function. Hamming window is used to pre-process the signal. It has been proved earlier that spectral features performs better than other features for videos signal classification [28]. Thus, in this paper the spectral features of videos are considered to model the VER system and the features are extracted by using MIR toolbox. After feature extraction of videos clips, classification process is conducted for LSTM networks layers as mentioned in section 2. The process flow of the system model is shown in fig. 3.

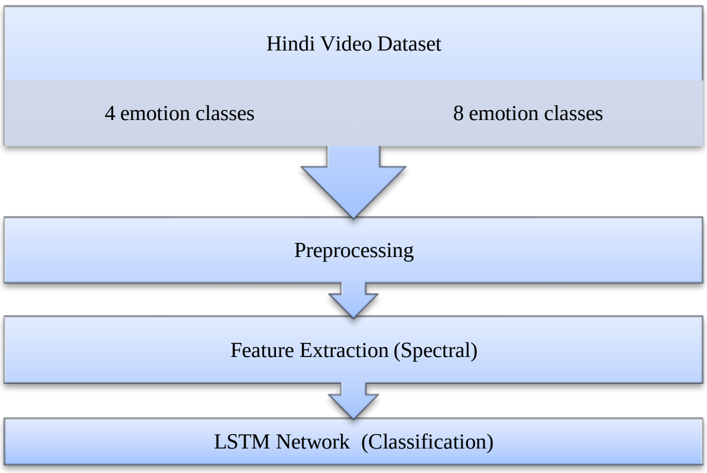

Figure 1 Process flow for system model

The dataset consisting of Hindi videos along with features is fed to LSTM layer. The features act as sequence data for the network. Four and eight emotion classes are considered for videos [28]. LSTM layer consists of number of hidden layers which are used to predict the information of data depending on the previous data stored. In this paper, the number of hidden layers is varied in order to check the performance of the modeled VER system. The performance of the system is evaluated in terms of accuracy and loss.

4. RESULTS AND DISCUSSION

The implementation of the proposed work is carried out by using MATLAB. The spectral features of video are in MATLAB. 1000 videos are considered in this research work. First system is modeled by considering four emotion classes i.e. PV-PA, NV-PA, NV-NA and PV-NA and second system is modeled by considering eight categories of emotion such as happy, aroused, tensed, frustrated, miserable, tired, sleepy and pleased. Spectral features are used to differentiate the defined classes. The dataset along with features considered as sequence data are fed to LSTM layer. In this presented work the number of hidden layers of LSTM network are varied to evaluate the performance of the modeled systems. Three experiments are conducted by considering depth of 40, 80 and 120 for the hidden layer. Weight gradients are calculated by using back propagation method to minimize the error. The accuracy and loss are considered as evaluation parameters for the proposed VER systems. In this proposed work, the training of the network is done by using Stochastic Gradient Descent with Momentum

(SGDM) optimization algorithm. The loss considered in this presented work is Half Mean Squared Error (HMSE).

During the training process of the system maximum number of epocs are set to 300 and min batch size is considered as 50. The base learning rate is set to 0.01. The evaluation results of the first system in which four emotion classes are considered are represented in table 1 and the evaluation results for the second system in which eight emotion classes are considered are represented in table 2. The accuracy achieved for the system 1 with 40 hidden layers is 89.6% and loss is 1.039. The accuracy for the system 1 with 80 hidden layers is 91.3% and loss is 0.591. The accuracy of the same system reaches 94.97% and loss is 0.021 with 120 hidden layers. The accuracy for the system 2 with 40 hidden layers is 85.3% and loss is 1.53. The system 2 achieves an accuracy of 88.40% with 80 hidden layers and loss achieved is 0.841. The accuracy of the same system reaches 92.8% and loss is 0.133 with 120 hidden layers.

Table 1 Accuracy and Loss for three observations for system 1

Experiment	Hidden Layer Depth	Accuracy	Loss
1	40	89.6%	1.039
2	80	91.3%	0.591
3	120	94.97%	0.021

Table 2 Accuracy and Loss for three experiments for system 2

Experiment	Hidden Layer Depth	Accuracy	Loss
1	40	85.3%	1.53
2	80	88.40%	0.841
3	120	92.8%	0.133

The graphical representation for accuracy and loss for system 1 is shown in figure 4 and observations for system 2 are shown in figure 5.

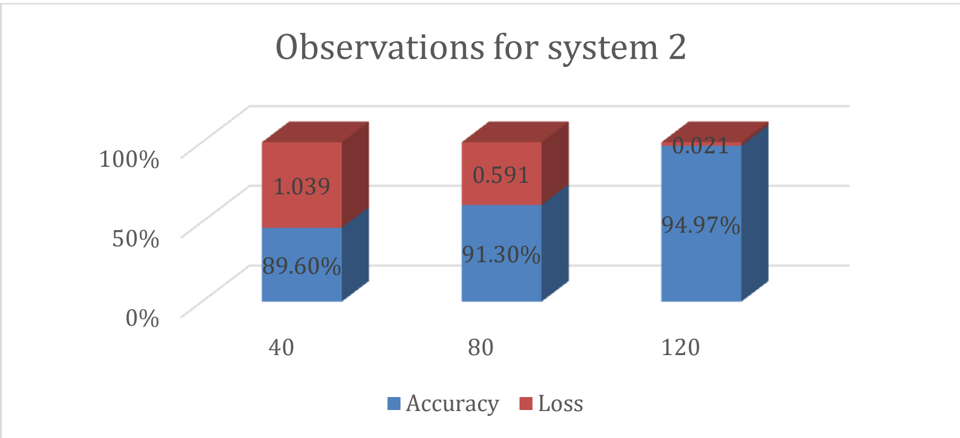

Figure 4 Graphical Observations for system 1

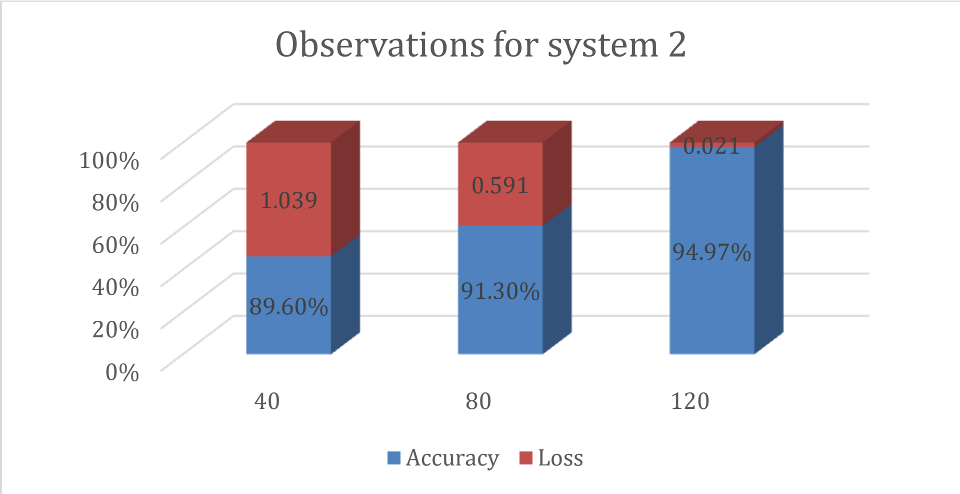

Figure 5 Graphical Observations for system 2

Thus, it has been concluded that the accuracy for both the systems is increased and error is decreased by increasing the number of hidden layers.

5. CONCLUSION

In this paper, VER system modeling is carried out by using LSTM networks to classify the Hindi videos in four and eight emotion classes. The system is tested by varying the number of hidden layers in the network. The number of hidden layers considered for conducting first, second and third experiment are 40, 80 and 120. Table 1 and 2 shows that the accuracy is raised with the increase in number of hidden layers. The accuracy for third experiment reaches 94.97% for system 1 and 92.8% for system 2. Results also reveal that the loss is decreased to 0.021 for system 1 and 0.133 for system 2. The results obtained in this presented work are satisfactory but there is always a scope of improvement. The VER system can also be modeled in future by using LSTM network with a greater number of emotion classes and by considering more features. Other parameters such as base learning rate, number of videos and number of LSTM layers can also be varied to model the system.

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