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Emotion classification for musical data using deep learning techniques

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ABSTRACT

This research is done based on the identification and thorough analyzing musical data that is extracted by the various method. This extracted information can be utilized in the deep learning algorithm to identify the emotion, based on the hidden features of the dataset. Deep learning-based convolutional neural network (CNN) and long short-term memory-gated recurrent unit (LSTM-GRU) models were developed to predict the information from the musical information. The musical dataset is extracted using the fast Fourier transform (FFT) models. The three deep learning models were developed in this work the first model was based on the information of extracted information such as zero-crossing rate, and spectral roll-off. Another model was developed on the information of Mel frequency-based cepstral coefficient (MFCC) features, the deep and wide CNN algorithm with LSTM-GRU bidirectional model was developed. The third model was developed on the extracted information from Mel-spectrographs and untied these graphs based on two-dimensional (2D) data information to the 2D CNN model alongside LSTM models. Proposed model performance on the information from Mel-spectrographs is compared on the F1 score, precision, and classification report of the models. Which shows better accuracy with improved F1 and recall values as compared with existing approaches.

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1. INTRODUCTION

In human-to-human communication, emotion plays a significant role because human contact does not include only language but contains non-verbal clues like gestures of the body, tones of voice, hand gestures, and facial expressions [1]-[3]. Thus, in various fields, such as applications in a call center, psychology, and text-to-speech engines, emotion recognition has been an essential inter-disciplinary research topic. Nowadays, emotion in music, audio, or lyrics plays a vital role in day-to-day human life and even more so in the digital age. There is a strong relation between music and emotion. Over the last quarter-century, many researchers recognized and classified emotion in music [4], [5]. In music information retrieval (MIR), automatic emotion recognition from music is an active task. There are many applications for music emotion reorganization in the field of music information retrievals, such as classification of the music emotion, music generation, instrument recognition, music source separation, and music recommender system. Consequently, emotion-based MIR attracted attraction in fields such as academia and the industry. In the academic emotion analysis of music, signals involve mood track, music sense, mood cloud, and moody. On the other side, from the field of industry, MIR also received attraction because many music companies use emotion as a cue for MIR, which are stated as grace notes, mood logics, mouseovers, and syntonic industries [6], [7]. Determination of the emotional category of music from audio or lyrics is quite challenging due to emotion labeling of music excerpts, feature extraction from the audio signals, and choosing the classification algorithm in the music emotion recognizing (MER) system. A music information retrieval subpart represents a MER system. The MER system has multiple application regions in emotion recognition, for example, suggestion systems for music, the creation of music playlists automatically, and music therapy. Music emotion recognizing systems build up with the music databases. There are two types of approaches in the MER system for databases: categorial and dimensional. The dimensional approach contains two-dimension valence and arousal. On the other side, emotions for the categorical approach are characterized as sad, happy, angry, and fearful [8]-[11]. There is the main aim of the music emotion reorganization system is to define the appropriate content of music by using deep learning or machine learning algorithm for classifying the emotion from music signals and signal processing techniques such as discrete Fourier transform and fast Fourier transform, respectively, for converting windowing frame into magnitude spectrum. For effective emotional recognition in music most widely utilized, energy-based features are perceptual based linear prediction cestrum coefficients (PLPCC), Mel frequency-based cepstral coefficient (MFCC), Mel energy-based cestrum dynamic coefficients (MEDC), and linear predictor coefficients (LPC) respectively [12]. Further, the emotion recognition for lyrics feature is based on natural language processing. Natural language processing uses various text classification methods for feature extraction from text data. The final stage of emotion recognition from audio or lyrics is the classification stage classification, and the most recent work addresses emotion classification by machine learning or deep learning. Deep learning algorithm-based models are stated as the deep belief network (DBN), deep convolutional neural network (DCNN) [13]-[15], deep neural networks (CNN or DNN), long short-term memory (LSTM), and on another side machine learning algorithm-based model is Naive bayes classifier, Gaussian mixture model (GMM), random forest algorithm (RF), K-nearest neighbor (KNN), support vector machine (SVM) are used as a classification model for music emotion recognition [16], [17]. Also, the emotion classification from the music has been done using a combination of various models represented as a multi-modal such as bidirectional encoder representations from transformers (BERT) and LSTM, CNN and LSTM, and CNN and Bi-LSTM. Using the multi-modal emotion classification model improves model accuracy for the emotion classification in both audio and lyrics [18]-[20].

Music emotion detection is a challenging task because emotions are subjective [21]. So, an optimized approach is required to improve the music emotion recognition accuracy. The major contribution of the presented methodology is to recognize the emotions of music with enhanced accuracy. The recognition accuracy generally depends on the effective feature extraction as well as on the selection of the features. Therefore, the proposed methodology uses the innovative pre-processing approach and also develops a hybrid form of classifier for emotions classification. Motivation, by summarizing music emotion classification (MEC), getting an idea that MEC is the essential technique for dealing with huge amounts of information about music. Using a traditional algorithm-based method for music emotion classification has a disadvantage because it is time consuming for music emotion recognition and has low accuracy; thus, single-model analysis can't fully express music emotion, so utilizing the multi-model analysis for the music emotion recognition from the audio signal [22]-[24]. Therefore, fast learning speed and high classification accuracy are achieved with music emotion classification by using a multi-modal fusion model research analysis based on audio cues. The performance measurement of multimodal fusion model analysis and dynamic classification performance could be improved by using a fusion of emotional information in music audio. Thus, in this research work for music emotion classification deep learning algorithm-based convolutional neural network (CNN) and ensemble of the LSTM-GRU model was utilized. Where the feature extraction process is done by the CNN and the emotion classification process is done by the ensemble LSTM-GRU model.

2. RESEARCH METHOD

2.1. Data collection

For this research work, we used the music emotion classes dataset and the dataset available on Kaggle open source data. Using this music emotion classes dataset performing music emotion classification for different emotions. The dataset consists of 10,133 data samples, which contain 5 different emotions from music signals namely, happy, sad, romantic, dramatic, and aggressive. A dataset consisting of various audio features and MFCC features for musical clips. Also, in the dataset MFCC feature consisting 20 MFCC coefficients.

2.2. Data visualization

We analyze five different emotions happy, aggressive, sad, romantic, and dramatic in a percentage of the music emotion classes. Dramatic and happy emotions get higher percentages such as 23.5% and 22.2% respectively compared to the other three emotions from the audio and MFCC features. After analyzing a correlation between the audio feature, plotting to scatter plot between the 1. Spectral bandwidth and zero-crossing rate 2. Chroma short-time Fourier transform (STFT) and spectral roll-off for the five types of emotion. Based on the above clustering figures of the cluster of different audio emotion categories based on the various features and all these characteristics are further utilized in the deep learning model for the different emotion pattern recognition based on various features.

2.3. Proposed methodology

A CNN is based on a deep learning algorithm technique. CNN is solely based on the SoftMax unit for classification purposes. CNN is commonly used to analyze visual images like facial recognition, pattern recognition, image processing, and object detection which provides a better classification of data. The CNN is a systematic neural network structure with multiple layers. A CNN consists of three layers, stated as a: i) convolution layers, ii) pooling layers, and iii) a fully connected layer and a SoftMax unit consist of two-dimensional planes. CNN builds the input by extracting feature pipeline modeling as an abstract. In CNN, one or more convolutional layers are utilized. The convolution layer produces a feature map consisting of the number of filters. During the convolution process, each local feature is first calculated using a convolutional kernel and the convolution kernel consists of height and bias. Each local component of the input vector convolved with the filter, which is the base of regional connections. A single convolution kernel represents the weight and height W and F respectively, input vector and bias represent with Xi and Ni respectively. After that, obtaining the output of the convolution layers by applying an activation function rectified linear unit (ReLU) or a non-linear methodology. Finally using the ReLU activation function or non-linear methodology computing the final convolution feature. The output of the convolutional layer passes to the pooling layers. After the convolution layer ri process, the pooling layer's aim is to reduce pattern resolut ion numbers and reduce the computational load by taking the mean values of each and every subsection of the n*n matrix. During the pooling layer process, the expanse of all the feature maps is done by the max-pooling operation using filter size. Like any other neural network, in the input layer the fully connected layers, hidden layer, and output layer must be fully connected layers. The resulting outcome of the pooling layer process is passed to a fully connected layer and classified by the soft max unit when the flattened layer transforms the feature into a feature vector.

2.4. CNN and LSTM model layers and configurations

2.4.1. A deep learning model was developed based on the audio features dataset

For this model the following 6 features of the extracted musical data are utilized to train the model. The music attributes are generally organized into a four-eight number of diverse classifications and each category specifies various concepts. The names of the categories include dynamics, tone color-timbre, rhythm, harmony, musical form, melody, musical texture, and expressive techniques.

- Chroma STFT
- RMSE
- Spectral centroid of the music
- Spectral bandwidth of the music
- Roll-off features
- Zero crossing rate of the music

Based on this information audio files features were trained with the CNN and LSTM Bi-direction models with the categorical cross-entropy of loss functions. Table 1 consisting the information about the CNN-LSTM model parameters for the various audio features. For this model the first embedded layers were utilized to combine the two deep learning models CNN with the LSTM Bi-directional model. the initial vector of the emending vector is 32. The sequential models of 64 filters, 5*5 kernel size, an activation function is ReLU with the 1-D convolution layers. Further, the layer and information are max pooling and reducing the filter size by 4*4 filters and flattening the model information by the bi-directional LSTM model which is configured by 400 gated recurrent unit (GRU) perceptron of the LSTM model. After this embedding the CNN and LSTM models. Figure 1 shows the training and validation accuracy and loss of the first model trained with various music extracted features.

Table 1. CNN-Bi-LSTM model for the MFCC features

Layer (type)	Output Shape	Param
Embedding layer (Embedding)	(None, 20, 32)	16,000
Conv1d_1 (Conv1D)	(None, 20, 64)	10,304
Max_polling1d (Max Polling 1D)	(None, 5,64)	0
LSTM (LSTM)	(None, 300)	438,000
Dense 1 (Dense)	(None, 256)	77,056
Dense_2 (Dense)	(None, 128)	32,896
Dense_3(Dense)	(None, 64)	8,256
Dense_4 (Dense)	(None, 5)	325

Total params: 582,837
Trainable params: 582,837
Non-trainable params: 0

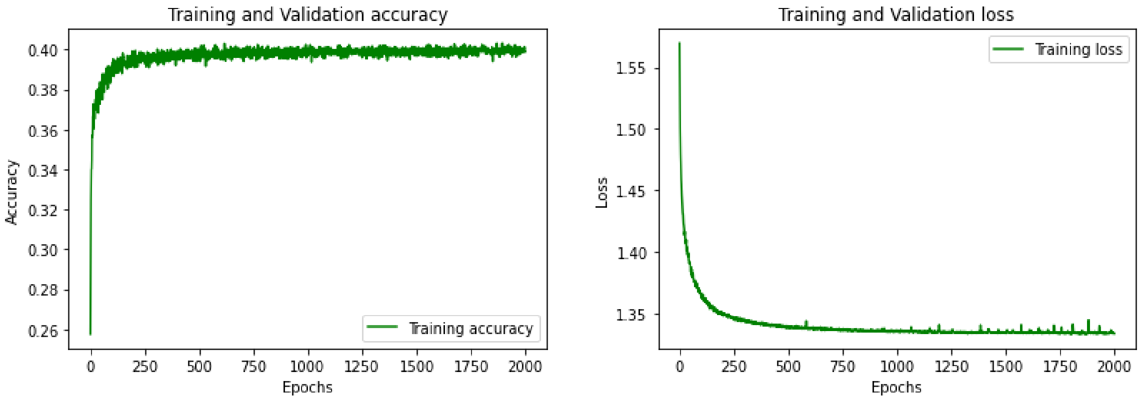

Figure 1. Training accuracy and loss of the first model trained with various music extracted features

2.4.2. Deep CNN and LSTM model

Deep CNN and LSTM model for the MFCC channel dataset are utilized with the 20 MFCC channels, all these features are thoroughly analyzed by statical analysis, and based on this information the deep learning hybrid model was developed. From Figure 2 training-validation accuracy and loss of the model trained with the MFCC features can be depicted. Table 2 shows the CNN-Bi-LSTM model parameter for the MFCC feature. This developed model is configured very similarly to table 1 but the configuration of the deep learning models and the embedding layer of the model were reconfigured based on the dataset information. The model is reconfigured with the 32 filters with the exponential increase in the filter size with the max pooling layer of the configuration of 64 filters for the extraction of the dataset. The dataset consists of 20 features which are more than the first model so the filers are able to extract a greater number of features with the embedding Bi-directional LSTM model the model configuration is displayed in Table 1.

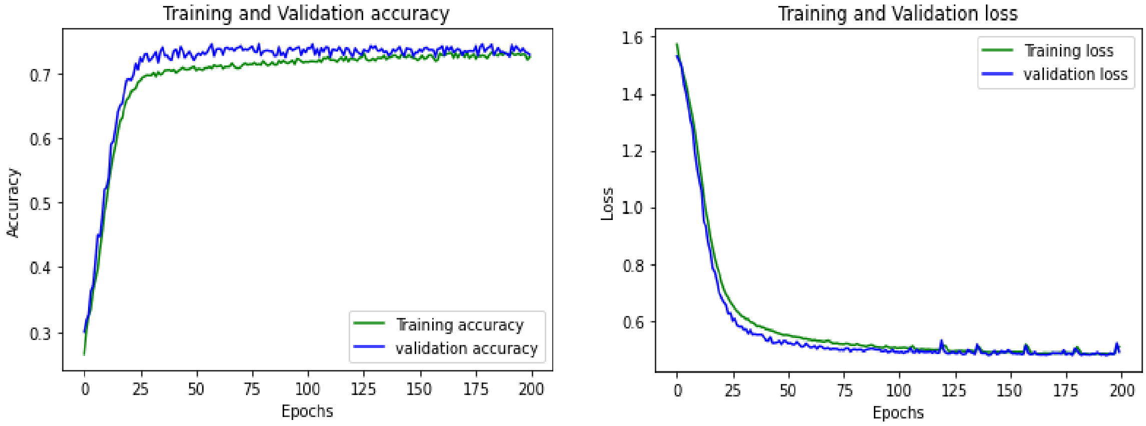

Figure 2. Training-validation accuracy and loss of the model trained with the MFCC features

Table 2. First model classification report (performance analysis)

Class	Precision	Recall	F1-score	Support
0	0.44	0.32	0.37	487
1	0.42	0.27	0.33	578
2	0.32	0.68	0.45	576
3	0.37	0.24	0.29	408
4	0.85	0.61	0.71	485
Accuracy			0.73	2534
Micro Avg	0.75	0.73	0.73	2534
Weighted Avg	0.75	0.73	0.73	2534

Dataset used: international society for music information retrieval 2012 dataset (ISMIR2012) [25]. The ISMIR2012 is a popular music dataset used for emotion recognition that consists of various types of songs in two languages, English and Hindi. The total numbers of songs in the English language are 2886 in which sad songs are 759, 746 are happy songs, 636 are angry songs, and relaxing songs are 745. Similarly, the total number of songs in the Hindi language is 1037 in which 200 songs are happy, 216 songs are sad songs, 283 songs are angry and 338 songs are relaxing. The collection of emotional songs is used for the categorization of different emotions.

3. RESULTS AND DISCUSSION

As shown in the Figure 1 model 1 were developed based on the musical features which are able to achieve training accuracy up to only 40% and features get stuck into the local minimum condition of the model in which the training parameters and the weights of the model get saturated due to sometimes fewer numbers of epochs or due to fewer features of the training parameters which is why this model gets stuck at 40% of accuracy and loss is get saturated so based on this parameter the model cannot be trained or tuned for the prediction and analysis of the emotion detection from the musical information.

The second model were developed based on the information and the data of musical information extraction based on the MFCC 20 channel features. These 20 features of the music are able to extract a greater number of hidden features from the models however the extracted information from the model. however, this model is developed with 200 epochs but when the training cross 100 epochs the model is going to get saturated with the 72% of model accuracy and stuck with the limited information about the musical features, so based on these two conditions of the model 1 and the model 2 it is very clear that for the indentation of the emotion from the music more numbers of hidden features needed to be extracted so for that purpose the Mel-spectrographs is utilized in the third model. Classification report of model trained with MFCC information can be analyzed in Table 3.

Table 3. Classification report of model trained with MFCC information

Class	Precision	Recall	F1-score	Support
0	0.62	0.74	0.67	487
1	0.68	0.83	0.75	578
2	0.88	0.67	0.76	576
3	0.71	0.80	0.76	408
4	0.85	0.61	0.71	485
Accuracy			0.73	2534
Micro Avg	0.75	0.73	0.73	2534
Weighted Avg	0.75	0.73	0.73	2534

In the third model the Mel-spectrographs of the music is utilize to train the model based on the outcome of the first two models. Training accuracy and loss of the third model with the Mel-spectrographs of the musical information can be depicted from Figure 3. This third model is trained with the 210 epochs which are able to generate 94% accuracy during the model training and during the model validation and testing the average and weighted accuracy is around 95% which can be analyzed in Table 4. These Mel-spectrographs are 2D type datasets so for this purpose the 2D CNN model has utilized this model extract a greater number of hidden features by applying multiple filters to the dataset which is not possible for the 1D data utilized in the above two models which is why this model is able to generate better prediction accuracy than the other two models.

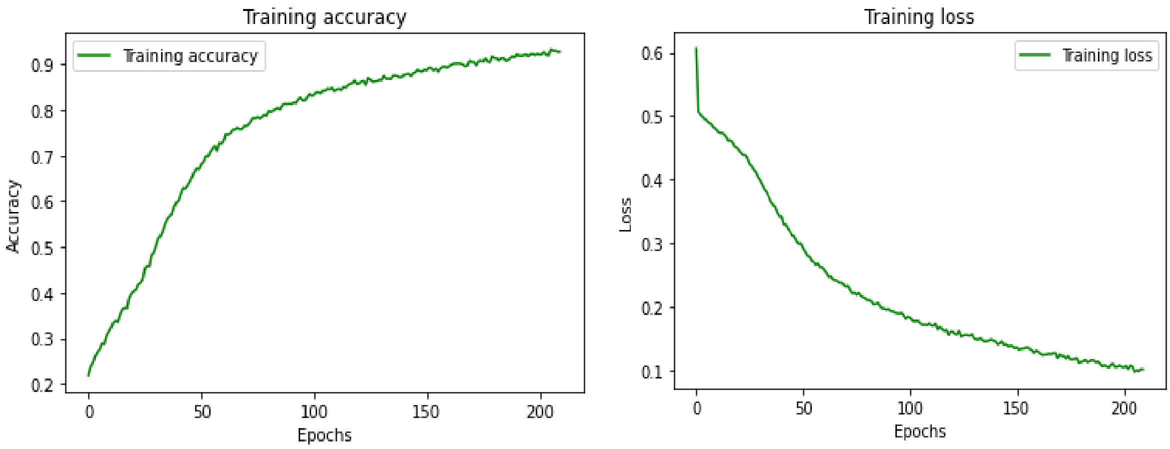

Figure 3. Training accuracy and loss of the model with the Mel-spectrographs of the musical information

Table 4. Model performance on the information from Mel-spectrographs

Class	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	620
1	0.90	1.00	0.95	735
2	0.92	1.00	0.96	633
3	1.00	0.88	0.94	493
4	1.00	0.85	0.92	559
Accuracy			0.95	3040
Micro Avg	0.96	0.95	0.95	3040
Weighted Avg	0.96	0.95	0.95	3040

4. CONCLUSION

With the development of the deep learning algorithm-based technique and digital technology for audio, the musical emotion recognition (MER) system has gradually emerged as the research hotspot. At present, for the MEC problem deep learning techniques are gradually mainstream. The focus of the music emotion classification research is to design a proficient and robust model for the recognition of emotion. So, this research work provided a detailed review of deep learning-based architecture and acoustic features for the music emotion classification. The proposed method is evaluated on the music emotion classes datasets. These deep learning algorithm-based models and their layer-wise architectures are explained in detail based on the classification of various emotions as dramatic, happy, aggressive, sad, and romantic. Therefore, proposing a CNN and an ensemble of LSTM-GRU method for a music emotion classification. First audio and spectrogram feature extracted from music signal. Here we examined various feature extraction techniques based on audio features and spectrograph features. After that create additional training samples from spectrogram images through the data augmentation process. Here, the CNN performs feature extraction from the spectrogram images. Here we performed a deep learning algorithm-based model for both audio and spectrograph features and from this analysis, the deep learning-based model for spectrograph feature obtained higher accuracy than the audio feature.

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