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Elevating sentiment analysis with deep convolutional neural network model facial expression insights

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ABSTRACT

In today's data-driven world, the ability to analyze emotional responses is essential. The pressing necessity that drives this study is to revolutionize the field of sentiment analysis by extracting the hidden information from people's facial expressions. It examines people's preferences, worries, and pleasure, revealing their views on many topics. Beyond text-based sentiment analysis, this research adds facial expression-based sentiment analysis into existing systems for tailored recommendations and mental health monitoring. The system emphasizes visual stimuli's emotional influence to improve decision-making, content adaptability, and user experiences. The implementation involves transfer learning with the pre-trained VGG-16 model, which enhances ability to discern intricate emotional cues from facial expressions. Convolutional neural network (CNN) and contextual analysis allow the model to understand users' emotions and provide insights into their thoughts, feelings, and behaviors. To improve emotion recognition reliability and reactivity, this study examines random forest, support vector machine (SVM), and CNN methodologies. The visual geometry group (VGG-16) CNN model outperforms over SVM and random forest classifiers with accuracy of 95%. This study highlights facial expression-based sentiment analysis.

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1. INTRODUCTION

The emergence of the internet and other digital technologies has brought about a new era of communication that heavily relies on facial expressions. Whether it's for entertainment, education, or interpersonal interactions, visual media plays a significant role in everything to do. With the proliferation of facial expression-sharing apps, social media platforms, and electronic communication, it has become essential to accurately interpret the emotional content conveyed through visual imagery. The impact of emotions on well-being and decision-making is evident in various aspects of our lives, including our physical and mental health. The ability to capture and understand emotions has numerous potential applications, ranging from improving mental healthcare to developing compassionate artificial intelligence (AI)-driven interactions. Traditionally, sentiment analysis focused on analyzing textual data, such as words and phrases, to gauge emotional tones. However, gaining a deeper understanding of human emotions requires more than just textual analysis.

The ability for robots to understand and interpret human emotions in multimedia environments is a major goal of the field of sentiment analysis. At its foundation, it is the process of identifying and classifying people's feelings, thoughts, and attitudes regarding particular persons, products, events, or topics [1]. Despite the advancements in sentiment analysis, accurately deciphering emotions from images continues to be a major hurdle. The intricate complexity of human facial expressions, along with the variations in lighting conditions and angles, significantly hinder the effectiveness of existing methodologies. Consequently, there is a pressing need for a robust solution that can discern emotions with unparalleled accuracy and reliability. Sentiment analysis has come a long way since its early days. Research in sentiment analysis has advanced significantly with the growth of new venues, such as blogs and social media, where individuals regularly share their ideas [2]. Social media's pervasiveness has brought the world's population closer together, allowing for the uninhibited exchange of ideas [3]. By utilizing the advanced capabilities of visual geometry group (VGG-16), cutting-edge convolutional neural network (CNN) architecture renowned for its exceptional image recognition and feature extraction abilities, aimed to delve further into the intricacies of facial expression analysis. The driving force behind our study originates from the recognition of facial expressions as a universal language of emotions that surpasses linguistic and cultural barriers. Through harnessing the valuable insights provided by facial expressions, our objective is to improve the accuracy and granularity of sentiment analysis, ultimately leading to a deeper comprehension of human emotions.

Every aspect of sentiment analysis how it is conducted, the data it uses, and the questions it asks—is evolving as a result of technological developments. In the early 2000s, researchers began using simple techniques like keyword-based analysis to determine if a piece of writing should be classified as positive, negative, or neutral. The development of natural language processing (NLP) tools, however, has ushered in a new era of sentiment analysis, marked by more refined approaches. Accuracy was improved by employing machine learning methods and features like n-grams and syntactic structures. Due to the immediacy and informality of user-generated material, the rise of social media platforms in the late aughts presented new issues. Improvements in sentiment analysis can be attributed in large part to the introduction of cutting-edge methodologies, such as lexicon-based systems that calculate sentiment scores and classify evaluations into positive or negative categories [4]. Support vector machines (SVM), naive bayes, and neural networks have become popular methods for sentiment analysis since the advent of machine learning and deep learning [5]. While aspect-based sentiment analysis made it possible to pinpoint opinions about individual items in text, domain adaption techniques worked to enhance sentiment analysis in general [6]. Sentiment analysis in multiple languages was a problem that multilingual sentiment analysis set out to solve [7]. It is still evolving as a method for gaining understanding from a wide variety of textual data in numerous fields and languages.

In light of these advancements, the proposed method may benefit from this study to provide a detailed comparison of the many algorithms such as SVM, VGG-16 CNN, and random forest for predicting the sentiment analysis. The proposed work also recommends creating a facial expression-based sentiment analysis algorithm for properly gauging and reacting to people' emotions and moods with digital world. In fields like mental health, where understanding and managing emotional states is crucial to individual well-being, this approach has the potential to dramatically boost our ability to give effective assistance and therapies. The key goals of this study are to develop a facial expression-based sentiment analysis model that is capable of recognizing and categorizing user emotions based on input frames of facial expression expressions. The integration of computer vision and sentiment analysis is underscored, recognizing the harmonious connection between these disciplines in offering valuable insights into human sentiment and behavior. In this study, a proposed method will be utilized to examine the sentiment analysis VGG-16 CNN, SVM, random forest algorithms. These algorithms will be evaluated and compared using various metrics including accuracy, precision, recall, and F1-score, to determine their relative rankings w.r.t accuracy and granularity of sentiment analysis.

2. LITERATURE SURVEY

The purpose of this literature review is to present a summary of current studies conducted in the field of sentiment analysis, with an eye toward how these studies relate to our own. The information gleaned from this survey will be invaluable in determining the course of our future studies. The authors suggest a lexical knowledge-based extraction strategy to achieve this comprehension from video transcriptions. They employ SenticNet to parse MuSe-CAR data for linguistic concepts and refine a number of feature types. They used the MuSe-automobile dataset to do research on sentiment analysis in the context of YouTube facial expression automobile evaluations. They used the Senticnet framework and a machine learning strategy based on SVM, achieving a combined metric of 66.16% on the test set and 56.18% on the development set. Surprisingly, their SVM-based model performed better than long short-term memory (LSTMs) units, popular neural network architecture, by more than 30%. The best model they present increases the linguistic baseline from the

MuSe-Topic 2020 sub-challenge by roughly 3% (absolute) in the prediction of valence on the standard challenge measure [8].

In a different piece of research, author suggested a deep neural network (DNN)-based model for sentiment analysis. In order to train their AI model, they used facial expression data from the YouTube channel 'Joice Hasselmann', from which they extracted opinion elements from raw text comments and then sorted them into discrete categories along a continuous scale from 1 to +1. The 84% accuracy achieved by their 6-layer DNN on the test set is indicative of the model's robust predictive capacity. To possibly improve results, the authors advised additional data preprocessing [9].

This study investigates the potential of gated recurrent units (GRUs), recurrent neural network architecture for assessing emotional valence in textual input. It suggests an extensive review of the use of deep learning methods for sentiment categorization and analysis. The Amazon review dataset was used to create several baseline models, such as LSTMs, GRUs, bidirectional long short-term memory (Bi-LSTM), and bidirectional gated recurrent unit (Bi-GRU). In contrast to LSTM, GRU were found to be more effective and to have shorter training times. Accuracy of 71.19% was achieved by the Bi-GRU, with remarkable precision, recall, and F1 scores of 71.3% each [10].

CNN were recently studied and highlighted its usefulness in sentiment analysis and how they can capture hierarchical patterns in textual data. CNNs used for analyzing English and Chinese text and found that the former had a 92% accuracy rate and the latter had an 87% accuracy rate. When applied to Hindi movie reviews, it showed exceptional adaptability across languages, obtaining 95.4% accuracy [11]. Authors presented the word2vec and CNN framework for the purpose of sentiment analysis; they entered this data into a CNN architecture using normalization and dropout techniques. On a dataset consisting of critical assessments of films, their model outperformed RNNs and MV-RNNs with a test accuracy of 45.4%. Their findings highlighted the significance of pre-training and fine-tuning for accuracy in CNNs [12], [13]. Using a CNN, researcher was able to classify images with an accuracy of 72.40% during validation. The accuracy of the model was dramatically raised to 95.40% with the use of image enhancement techniques and transfer learning using the VGG-16 pretrained model. This proved the value of using pretrained models like VGG-16 for improved image categorization [14]. Authors suggested a CNN-based approach that merged text and image data in tweets for sentiment analysis, with accuracy rates of 78% and 79.6% on various datasets, respectively, exceeding conventional techniques. By highlighting the capability to grasp intricate correlations between text and images, their study bridged the gap between CNNs' triumphs in text and image sentiment analysis [15]. A study on picture classification in which they used a number of different classification models in conjunction with deep features retrieved with the VGG19 CNN. Compared to other classifiers and approaches, random forest's combined feature accuracy of 93.73% is striking. A combination strategy for picture categorization was proven beneficial in this study [16]. The applicability of various deep learning models for sentiment analysis of images, including DNNs, CNN, region-based convolutional neural network (R-CNNs), and Fast R-CNNs investigated. According to their research, CNNs are more productive and precise than competing networks [17]. SVM and CNN were compared for image classification. While SVM performed well on a tiny dataset, CNN performed much better, with an astounding 93.57% accuracy on the same dataset [18]. The "Viola Jones face detection" technique was used for face localization in a work on facial expression identification and sentiment analysis. Zernike moments, linear binary patterns, and the discrete cosine transform were among the feature extraction techniques and classifiers employed. On the JAFFE database, their algorithm recognized 90.14% of the images [19]. The CNN was used to extract features from the images, and the VGG was used to analyze the emotions conveyed in the photo. The classification of buccal squamous cell carcinoma with VGG16 achieved an accuracy of 83.33 percent on training data [20]. This literature review covers a wide range of studies and methods within the field of sentiment analysis, with a focus on how deep learning methods, CNN, and the combination of text and image data have contributed to the development of sentiment analysis in a number of contexts and languages.

3. PROPOSED METHODOLOGY

Recommended strategy is built on utilizing the powerful architecture of CNNs to create a facial expression-based sentiment analysis model. The goal is to automatically recognize and understand the range of emotions conveyed by facial expressions using CNN. Autism spectrum disorder, anorexia, and other forms of teenage mental disease can be predicted using sentiment analysis applied to current data gathered from social networking sites [21]. In order to effectively distinguish and categorize a wide range of emotions, the model will be trained using a dataset of facial expressions.

3.1. System design

The suggested model, as seen in Figure 1, starts with data collection—in this example, pictures of faces with expressions that represent different emotions. Facial expression recognition and audio processing are two strategies used in the feature extraction process to retrieve relevant data. The VGG-16 CNN algorithm is divided into number of sub processes like pooling layer, NLP, and regularization. The model is detecting mental health as a result with the proposed system.

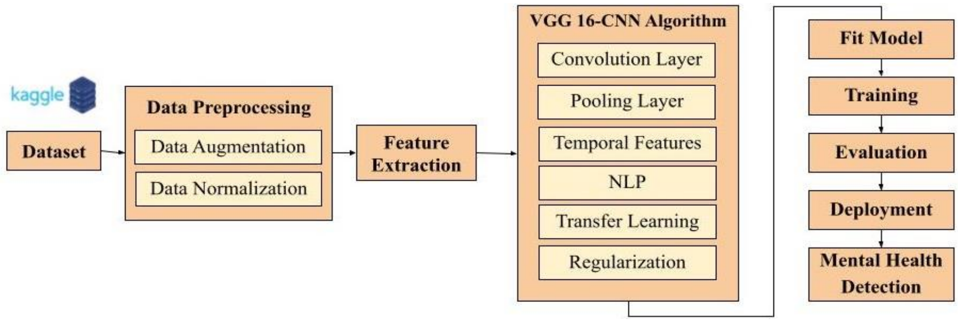

Figure 1. System architecture

3.1.1. Dataset

The first step in the proposed model as shown in Figure 1 is to collect data, in this case images of face expressions conveying various emotions. The process of feature extraction makes use of audio processing and facial expression detection to glean useful information. The dataset is gathered from Kaggle and it consists of 19 classes which contain 8 different types of emotions of different people. Images are categorized based on different kind of facial expression expressions like disgust, fear, happy, neutral, sad, surprised, anger and contempt. A dataset which is used for sentiment analysis purposes is likely to contain a variety of attributes or features related to sentiment, such as emotion-based images and their corresponding textual descriptions or annotations [22].

Data pre-processing encompasses steps like data normalization and data enhancement. TensorFlow's ImageDataGenerator to take care of pre-processing and data preparation for testing and training. The feature set is improved through feature selection and engineering, and the VGG-16 CNN model is used for sentiment analysis. The 'ImageDataGenerator' tool, found in the TensorFlow and Keras libraries, is frequently used for enhancing and pre-processing image data before to use in deep learning tasks. Using a CNN architecture that is good at capturing spatial data is crucial when classifying images. The primary splitting function is provided by the 'validation_split' argument. This information set is composed of 80% training data and 20% validation data. The next steps include training, validation, and hyper-parameter adjustment. Evaluation metrics including accuracy, precision, recall, and F1-score matrices are used to assess the performance of a model. Studying facial expressions can help predict emotions in real time, and response processes enable sympathetic dialogue. After that, future study areas in mental healthcare and content customization can be identified and incorporated into existing systems.

3.2. System implementation

The VGG-16 CNN as shown in Figure 2 has been trained on a massive and varied picture dataset, granting it the capacity to autonomously extract meaningful features from images using a series of convolutional and pooling processes. This model with pre-trained ImageNet weights using VGG-16. The proposed method has been opted to add more classification layers to it [23]. After developing a unique model, it is evaluated and refined with the help of a specific dataset. The CNN layers are discussed in following section.

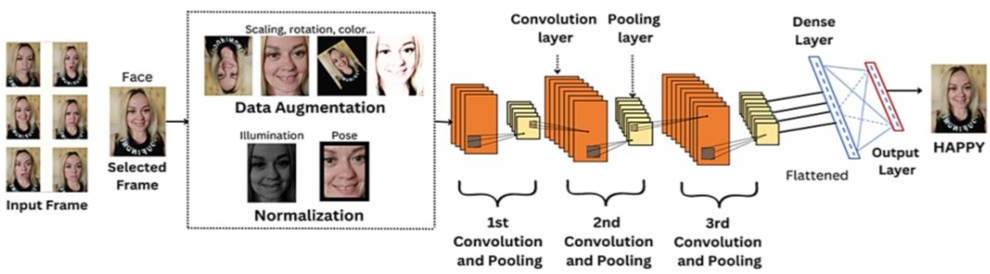

Figure 2. Emotion recognition using VGG16-CNN

3.3. Convolution layer

The convolutional layer is designed to acquire a range of features from the input, including edges, textures, patterns, and more intricate structures. These features are subsequently transmitted to succeeding layers for additional analysis. Convolutional layers offer significant advantages, such as the capacity to grasp spatial hierarchies within data, decrease the parameter count in contrast to fully connected layers, and facilitate the detection of translation-invariant features.

3.4. Pooling layer

Pooling layers, which function similarly to summarizers, are frequently used after this scanning procedure. They aid in distillation, allowing us to store only the most relevant details and dismiss the rest. This facilitates the model's ability to zero in on the most relevant portions of the data [24]. The convoluted image is calculated as shown in (1). The convolution process computes the output feature map Y from the input feature map (tensor) X and the convolutional kernel (tensor) W by element-wise multiplying and summing. Y is element-wise subjected to the ReLU activation function, as indicated in (2).

$$s(i,j) = \sum_m \sum_n (I(m,n)k(i-m,j-n)) \quad (1)$$

$$Y = max(0, Y) \quad (2)$$

The global average pooling layer is used to retain essential information while decreasing the spatial dimensions of the feature maps produced by the convolutional layers. Many models use it instead of regular fully linked layers to cut down on the number of parameters and the risk of overfitting. Given the feature map X from the previous layer, the global average pooling computes the average value along each channel (feature map) is derived from (3).

$$Yk = 1/H + W \sum_{i=1}^{H} \sum_{j=1}^{W} Xijk \quad (3)$$

Here, H and W are the height and width of the feature map.

3.5. Dense layer

Dense layers, also known as fully connected layers, are a fundamental component of neural networks used for classification and regression tasks. They serve to connect all neurons in one layer to all neurons in the subsequent layer. In the context of classification, the output of a dense layer often represents the scores or probabilities for each class. Given an input vector X and weight matrix W, the dense layer computes the output vector Y, b is the bias vector in (4).

$$Y = X * W + b \quad (4)$$

3.6. Activation function

The ReLU activation function is applied element-wise to Y: Y=max (0, Y) (for hidden layers). The softmax activation function is applied to the output layer to produce class probabilities. These equations represent the operations performed by the convolutional layers, global average pooling layer, and dense layers in the code you provided. The code uses TensorFlow, which handles the computation of gradients and updates to weights and biases during backpropagation automatically [25].

4. RESULTS AND DISCUSSION

VGG-16 CNN, SVM [26], and random forest were the three methods of sentiment analysis that were compared by researchers and contrast in Table 1. Accuracy is 95%, 74%, and 79% respectively. VGG-16 CNN is outperforming among all w.r.t precision, recall, F1-score and accuracy.

The model's accuracy is quantified by the percentage of training instances that were properly labeled. A high accuracy during training suggests that the model is successfully adapting to fit the provided data [27]. The correctness of the model's validation is evaluated by how well it performs on a different dataset known as the validation dataset. Instead of being used for training, this dataset is just used to evaluate the model's ability to generalize to novel data. If the model has good performance on data it hasn't encountered during training, it means the validation accuracy is high. In a perfect world, the model's learning and generalization abilities would be reflected in high and similar training and validation accuracy.

Table 1. The performance comparative of VGG-16 CNN, SVM, and random forest

Method	Precision	Recall	F1-score	Accuracy
VGG-16 CNN	0.95	0.93	0.94	0.95
SVM	0.68	0.90	0.67	0.74
Random forest	0.72	0.79	0.74	0.79

The accuracy of the model's predictions is evaluated during training by comparing them to the true labels. It is a common metric used to assess the degree of discrepancy between expected and observed outcomes. Training aims to reduce this loss as much as possible. Similar to training loss, but determined using the validation dataset, is validation loss. It evaluates how closely the model's predictions match the validation data's actual labels. Training loss should go down steadily in a good scenario, showing that the model is improving. The Figures 3 to 5 depicts the confusion matrix, graphical analysis of training and validation accuracy as well as loss with respect to the proposed model.

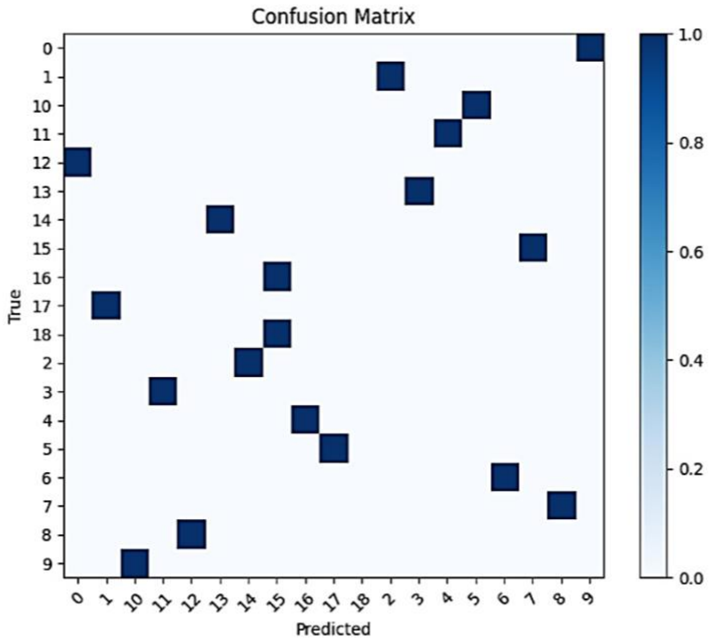

Figure 3. Confusion matrix

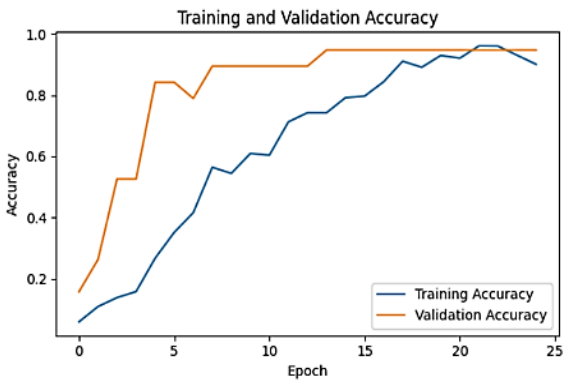

Figure 4. Training and validation loss

Figure 5. Training and validation accuracy

As was indicated in Figure 5, the accuracy reaches around 98%, which is in line with what is to be expected from a high-quality model. The loss also goes down and down until it's practically gone, which is a good thing and in line with our predictions. In addition, it can be shown that the model improves with more epochs, leading to better accuracy and less loss.

5. CONCLUSION

In this research, researchers took benefit of transfer learning by using CNN architecture, VGG-16 CNN, which had already been trained on the massive ImageNet dataset in order to improve our ability to decode the emotions conveyed by facial expressions. CNN from the field of computer vision play a central role in our novel approach, which has its origins in facial expression-based sentiment analysis. This innovative method exemplifies the vast potential of interdisciplinary cooperation in the field of sentiment analysis. Proposed system extracts relevant features from facial expression frames using pre-trained deep learning models like VGG-16 CNN which demonstrates the power of transfer learning in the field of sentiment analysis. To better understand the emotions contained in multimodal data, these traits were easily combined with NLP and contextual analysis. Proposed system is compared with SVM and random forest where VGG-16 CNN is proved excellent i.e. accuracy 95 %, precision 95%, recall 93%, and F1 score 94%. Affective computing, multimodal data integration, natural language creation, explainable artificial intelligence, and privacy-preserving approaches are all on the horizon for sentiment analysis, which bodes well for its bright future. These advancements have the potential to radically alter the field of mental healthcare by providing patients with more tailored, compassionate care that also respects their right to privacy.

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