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# Sentiment Analysis of Natural Disaster Images Obtained from Social Media: An Experimental Study

## Sosyal Medyadan Alınan Doğal Afet Görüntülerinin Duygu Analizi: Deneysel Araştırma

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**ABSTRACT Objective:** The frequency of natural disasters worldwide is increasing, and social networks have become popular sources of crucial data for analyzing images' emotions. Although the analysis of disaster-related images is a relatively new field, this study aims to identify the emotional responses evoked by images shared on social media. **Material and Methods:** In this four-stage study, a total of 5,203 free and openly accessible images were scraped from various social media platforms, and emotion categories associated with these images were selected. The images were converted to RGB format and resized after undergoing preprocessing. Normalization of the visual pixels was performed. Various deep learning (DL) models were examined for visual sentiment analysis, and their performance was compared using metrics. Subsequently, emotion classification was performed using Inception-v3, which yielded the most reliable results. **Results:** The most suitable DL model among different pre-trained DL models was determined to be Inception-v3 with a performance metric of 81.2%. The analysis of the emotions depicted in the images revealed that 71.9% (n=3,741) were classified as negative, while 8.0% (n=781) were classified as neutral. **Conclusion:** These results indicate that visual sentiment analysis of social media data can significantly enhance disaster response efforts. By identifying early warning messages, updating disaster-related information, and monitoring user-generated content, this approach supports more effective data analytics and information dissemination. Consequently, the use of advanced DL models like Inception-v3 in analyzing emotional content from social media can provide valuable insights and improve the efficiency and effectiveness of disaster management strategies.

**Keywords:** Social media; artificial intelligence; deep learning; sentiment analysis; natural disaster

**ÖZET Amaç:** Dünya genelinde doğal afetlerin sıklığı artmaktadır ve sosyal ağlar, görüntülerin duygusal analizi için kritik veri kaynakları hâline gelmiştir. Doğal afetlerle ilgili görüntülerin analizi nispeten yeni bir alandır, bu çalışma ise sosyal medyada paylaşılan görüntülerin uyandırdığı duygusal tepkileri tanımlamayı amaçlamaktadır. **Gereç ve Yöntemler:** Bu 4 aşamalı çalışmada, çeşitli sosyal medya platformlarından toplam 5.203 ücretsiz ve açıkça erişilebilir görüntü çekildi ve bu görüntülerle ilişkilendirilen duygu kategorileri seçildi. Görseller, ön işleme tabi tutularak RGB formatına dönüştürüldü ve yeniden boyutlandırıldı. Görsel piksellerinin normalizasyonu yapıldı. Görsel duygu analizi için çeşitli derin öğrenme [deep learning (DL)] modelleri incelendi ve performansları metrikler kullanılarak karşılaştırıldı. Daha sonra, en güvenilir sonuçları veren Inception-v3 kullanılarak duygu sınıflandırması yapıldı. **Bulgular:** Önceden eğitilmiş farklı DL modellerinin performans metrikleri içerisinde en uygun derin öğrenme modeli %81,2 ile Inception-v3 olduğu belirlendi. Görüntülerde tasvir edilen duyguların analizi, 3.741'i (%71,9) negatif olarak sınıflandırılırken, 781'i (%8,0) nötr olarak sınıflandırıldığını ortaya koydu. **Sonuç:** Bu sonuçlar, sosyal medya verilerinin görsel duygu analizinin, afet müdahale çabalarını önemli ölçüde artırabileceğini göstermektedir. Erken uyarı mesajlarını belirleyerek, afetle ilgili bilgileri güncelleyerek ve kullanıcı tarafından oluşturulan içeriği izleyerek, bu yaklaşım daha etkili veri analitiği ve bilgi yayılımını desteklemektedir. Sonuç olarak, sosyal medyadan duygusal içerik analizinde Inception-v3 gibi ileri derin öğrenme modellerinin kullanılması, değerli içgörüler sağlayabilir ve afet yönetim stratejilerinin verimliliğini ve etkinliğini artırabilir.

**Anahtar Kelimeler:** Sosyal medya; yapay zekâ; derin öğrenme; duygu analizi; doğal afet

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Floods, earthquakes, and other sudden and unexpected events pose significant public health concerns, causing damage to infrastructure and profound effects on people's physical and mental well-being. Access to relevant information in such events is crucial for assessing and mitigating damages. Satellite imagery, Geographic Information Systems, and social networks are widely used for analyzing the potential impact of natural or human-induced disasters on the environment and human life.[1,2] Given the frequent occurrence of natural disasters worldwide, which lead to both human suffering and economic losses, there is an increasing interest in utilizing social media data and sentiment analysis for disaster response. Social networks provide a two-way communication channel for acquiring and disseminating information related to disasters, making them invaluable for public health communication.[3] The systematic utilization of social media can bring advantages to emergency management by capturing requests for assistance from victims, monitoring user activities, and updating public awareness of the situation.[4] Sentiment analysis of social media imagery, conducted using deep learning (DL) methods of artificial intelligence, provides valuable insights into public health crises. Existing literature on visual sentiment recognition primarily focuses on analyzing facial expressions, background objects, and light and color contrasts to predict an individual's emotions based on image analysis.[5]

According to the Emergency Events Database (EM-DAT), there were 387 natural disasters and hazards in 2022, resulting in 30,704 fatalities and affecting approximately 185 million people globally.[6] Türkiye, in particular, has experienced profound impacts from disasters such as floods, earthquakes, and forest fires in recent years. Therefore, conducting sentiment analysis of the population becomes crucial for the mental well-being of the community. However, there are limited studies on this subject.[7] Some research discusses the application of DL methods for visual sentiment analysis of images obtained from social media platforms.[7-10] Others present fully automated algorithms for monitoring disasters from social media posts using sentiment analysis.[9] Focus is given to sensitivity analysis of Twitter data, particularly related to specific events.[10] The role of social media, especially Twitter, in emergency management during natural disasters is also explored, highlighting its use for information dissemination and data collection with specific case studies.[8] Analyzing the emotions, attitudes, and sentiments of individuals towards images related to these events can serve as an effective tool for conveying public sentiment globally. This study seeks to contrast DL approaches in the sentiment analysis of images related to natural disasters sourced from social media.

## MATERIAL AND METHODS

### DESIGN

This study utilized DL techniques to perform sentiment analysis on images depicting natural disasters. The flowchart outlining the sentiment analysis process is depicted in Figure 1.

The study consisted of four stages. Firstly, images related to disasters were gathered from social media platforms, including Facebook, Twitter, Instagram, and Flickr. Keywords such as floods, hurricanes, forest fires, droughts, landslides, and earthquakes were used on October 28, 2021, resulting in a dataset of 1,524 images. Additionally, a publicly accessible dataset created by Hassan et al. consisting of 3,679 natural disaster images was incorporated into the researchers' dataset.[7] In the second stage, emotion categories associated with disaster images were selected. The downloaded images were manually filtered to remove irrelevant ones, and the researchers annotated them. The images were preprocessed by converting them to the RGB format and resizing them to dimensions of $224 \times 224 \times 3$. Normalization of the visual pixels was performed.

In the third stage, the Convolutional Neural Network (CNN), a DL technique, and transfer learning using a pre-trained model on ImageNet were employed to automatically assign emotions to the images. The fourth stage encompassed the comparison and analysis of different DL models, specifically AlexNet, VGGNet, ResNet, and Inception v-3. Performance metrics, including accuracy, precision, recall, and F1 score, were employed

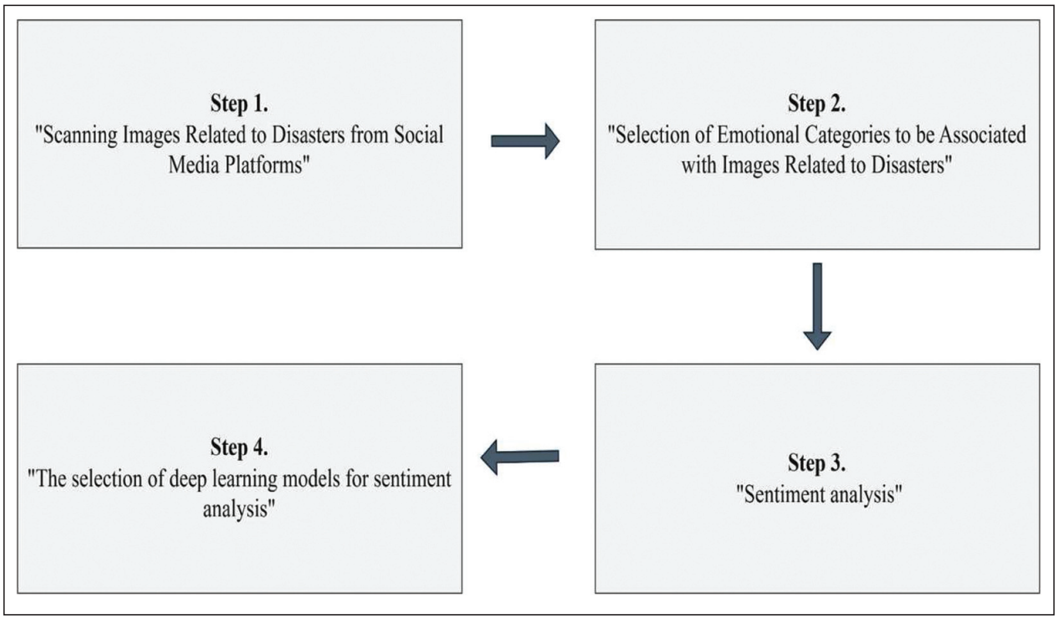


**FIGURE 1:** Flowchart of the study.

for evaluating the proposed visual sentiment analysis.

## SENTIMENT ANALYSIS

Emotions, which can be expressed through text, images, or videos, include feelings, likes and dislikes, or opinions. DL algorithms are commonly used for image sentiment analysis. A DL model can achieve accuracy and efficient task performance. The term "Deep" in DL refers to the number of hidden layers in neural networks. DL models are trained using a large labeled dataset and an architecture known as a Neural Network Architecture, which allows for the learning of features or parameters directly from the given data without any human intervention or manual feature extraction.[11] The primary task of an image sentiment analysis system is to predict the sentiment polarity of an input image in terms of two (positive, negative) or three polarity levels (positive, neutral, negative). Therefore, these approaches can be used for the task of polarity prediction.[12]

Polarity and subjectivity scores ranging from -1 to 1 and from 0 to 1, respectively, were calculated for the images. A subjectivity score of 0 indicated objectivity, while a score of 1 indicated subjectivity. Polarity scores between -1 and 0 were classified as negative, scores equal to 0 were classified as neutral, and scores between 0 and 1 were classified as positive emotions.

## PERFORMANCE METRICS

The performance evaluations of models trained with DL are conducted using accuracy, recall, precision, and F1 score. The explanations of the performance metrics are as follows:

**Accuracy:** The accuracy of a test is the ability to correctly distinguish between diseased and healthy individuals.[13] When calculating the accuracy of a diagnostic test, the true positive (TP) and true negative (TN) rates are computed for all diseased and healthy individuals. The accuracy value ranges from 0 to 1. In the notation given in (Formula 1), TP, TN, false positive (FP), false negative (FN).

Accuracy=(TP+TN)/(TP+TN+FP+FN) (Formula 1)

**Precision:** The precision value is calculated as the positive predictive value of a diagnostic test or the rate at which positive predictions are actually positive (Formula 2). In other words, it is defined as the probability that a person with a positive test result is actually diseased.

Precision=TP/(TP+FP) (Formula 2)

| TABLE 1: Confusion matrix. | | |
|---|---|---|
| | **Actually positive (1)** | **Actually negative (2)** |
| Predictied positive (1) | True positives | False positives |
| Predictied negative (2) | False negatives | True negatives |

**Recall:** Recall estimates how many TP the model captures (Formula 3). Similarly, when the cost of FNs is very high, recall is used as the metric to select the best model.

Recall=TP/(TP+FN) (Formula 3)

**F1 Score:** Depending on the problem being solved, in many cases, higher priority can be given to maximizing either precision or recall. However, a simpler statistic that takes both precision and recall into account is the F1 score, which is essentially the harmonic mean of precision and recall (Formula 4). Efforts are made to maximize this number to improve the model.

F1 Score=2x(PrecisionxRecall)/(Precision+Recall) (Formula 4)

Model performance can also be displayed in a confusion matrix. A confusion matrix is an n x n matrix, where n represents the number of labels in a given dataset. Each row represents the actual labels, and each column represents the predicted labels. The confusion matrix, as shown in Table 1, illustrates the performance of the model.

## DL MODELS FOR SENTIMENT ANALYSIS

### Transfer Learning

Transfer learning is a DL approach used to solve complex problems in computer vision. It enhances the performance of classification models by leveraging pre-trained models and accelerating the training of deep layers, thereby reducing computation time. Several transfer learning models are available, including AlexNet, VGGNet, ResNet, and Inception v-3, which have been trained on large datasets containing millions of images.

### AlexNet

AlexNet, developed by Krizhevsky et al., is a CNN model with 60 million parameters. It comprises eight layers, including five convolutional layers and three fully connected layers. The rectified linear activation function (ReLU) is utilized to mitigate gradient vanishing during model development. The model has been trained on 1.2 million high-resolution images from ImageNet, classified into 1,000 categories.[14]

### VGGNet

VGGNet is a deep CNN developed by researchers from Oxford University and Google DeepMind. It consists of six network models with depths ranging from 11 to 19 layers. The most commonly used sets are those with 16 and 19 layers, which excel in classification and localization tasks. The structure includes five convolutional layers.[15]

### Inception v-3

Inception v-3 is a CNN developed by Google as a module for image processing and object detection. It represents the third iteration of Google's Inception CNN. The model incorporates 25 million parameters trained on ImageNet. ReLU activation is utilized during model development.[16]

### ResNet

ResNet, proposed by He et al. addresses the issue of vanishing gradients during the training of deep convolutional networks.[17] It has demonstrated superior performance compared to other models in tasks such as object detection and semantic image segmentation.[18,19] The model utilizes input images with dimensions of 224×224×3 pixels and performs convolution (7×7) and max pooling (3×3) operations. Optimization and ReLU activation are applied after convolution.[17]

## DATA COLLECTION AND SELECTION OF EMOTION CATEGORIES

In this study, images for analysis were collected by scanning social media platforms, namely Facebook, Twitter, Instagram, and Flickr. Care was taken to ensure that all images were freely available and openly licensed. The selection of images was based on keywords such as flood, hurricane, forest fire, drought, landslide, and earthquake. Additionally, location information on earthquake occurrences in Türkiye was obtained from EM-DAT, a United Nations platform providing global disaster statistics.[6] For emotion categorization, the polarities of positive, negative, and neutral were chosen.

### SELECTION OF DL MODELS

The visual emotion analysis in this study employed the CNN model of DL. Transfer learning was also utilized. Four different DL models were employed: AlexNet, VGGNet, Inception-v3, and ResNet. These models were pre-trained on ImageNet for object features and on place for background details and scene-level features.[20,21] A high-speed sampling technique was utilized to balance the class distribution within the dataset. In single-label classification, the imblearn open-source library was used.

### EXPERIMENTAL SETUP

The dataset used in the experimental study was divided into training (70%), validation (10%), and test (20%) sets. The experiments were conducted on a computer with an Intel(R) Core(TM) i7 processor, 62 GB RAM, and a GPU GeForce RTX 2070 (8 GB). The evaluation of the DL models involved a comparative analysis of performance metrics, including accuracy, precision, recall, and F1 score.

### ETHICAL APPROVAL

Due to the nature of the research and the use of publicly available images, ethical permission was not required. The data collection process involved an automated method. As a result, this study has been conducted in accordance with the principles of the Helsinki Declaration.

## RESULTS

For the images used in this study, positive, negative, and neutral emotion categories were defined. Various elements within the images, including objects (such as clothing, collapsed buildings, background components, and signs), color/contrast, as well as human expressions, gestures, and poses, offered significant cues for the visual emotion analysis of disaster-related images. When analyzing the dataset, it was observed that 13.1% of the images exhibited positive emotions (n=681), 71.9% displayed negative emotions (n=3,741), and 15% were classified as neutral (n=781) in terms of polarity (Figure 2).

This study employed an early fusion approach, integrating object and scene-level features. The DL models used in this study were based on CNN, specifically AlexNet, VGGNet, Inception-v3, and ResNet. The performance metrics of these DL models are presented in Table 2. The accuracy values for different DL models pre-trained on ImageNet and Place were 78.12% for AlexNet, 77.52% for VGGNet, 81.17% for Inception-v3, and 79.03% for ResNet. Although there were no significant differences among the DL models, it was determined that Inception-v3 was the most suitable DL model for this study (Table 2).

The performance of DL models was evaluated in terms of accuracy, precision, recall, and F1 score for positive, negative, and neutral emotion poles. As illustrated in Table 3, Inception-v3 exhibits the highest accuracy for all three emotion poles among the models utilized in this study. Inception-v3, which employs a CNN structure, yielded the most precise results in sentiment analysis. As the model had been pre-trained, the weights that had been used in previ-

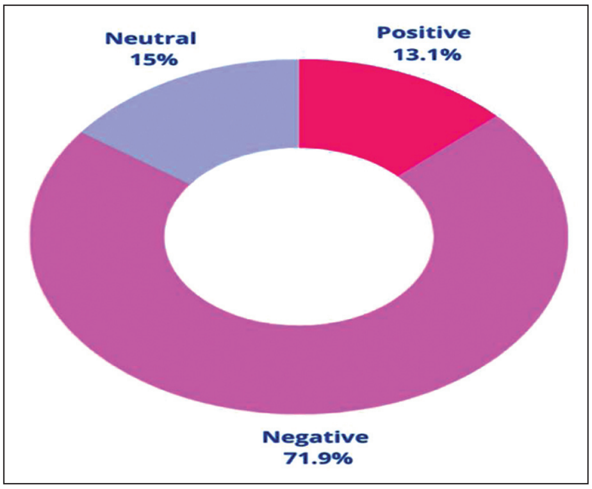


**FIGURE 2:** Statistics of emotion analysis for the dataset.

**TABLE 2:** Performance metrics of DL models.

| DL models | Accuracy | Precision | Recall | F1 score |
|---|---|---|---|---|
| AlexNet | 78.12 | 86.12 | 88.41 | 86.07 |
| VGGNet | 77.52 | 79.22 | 79.62 | 73.60 |
| Inception-v3 | 81.17 | 87.42 | 89.18 | 89.44 |
| ResNet | 79.03 | 86.91 | 73.52 | 81.23 |

DL: Deep learning.

| TABLE 3: Performance metrics analysis of DL models based on polarities. | | | | | |
|---|---|---|---|---|---|
| **DL models** | **Sentiment polarity** | **Accuracy** | **Precision** | **Recall** | **F1 score** |
| AlexNet | Negative | 79.12 | 88.17 | 81.54 | 79.85 |
| | Positive | 80.13 | 85.65 | 82.69 | 79.65 |
| | Neutral | 81.22 | 87.96 | 82.98 | 81.56 |
| VGGNet | Negative | 78.14 | 82.36 | 81.23 | 89.65 |
| | Positive | 78.45 | 83.65 | 79.45 | 82.51 |
| | Neutral | 79.65 | 84.56 | 79.84 | 81.44 |
| Inception-v3 | Negative | 89.43 | 90.12 | 90.07 | 80.69 |
| | Positive | 89.61 | 91.56 | 93.69 | 94.51 |
| | Neutral | 88.74 | 89.74 | 88.94 | 85.77 |
| ResNet | Negative | 81.26 | 93.25 | 91.65 | 89.74 |
| | Positive | 80.98 | 88.88 | 80.23 | 84.71 |
| | Neutral | 80.54 | 84.72 | 85.23 | 85.44 |

DL: Deep learning.

ous training were used as a basis for reconstructing the model with the current data. During the transfer learning process, the final classifier layer was modified to classify positive, negative, and neutral emotions. The smoothing layer added to the final classifier contains nodes representing the three emotion categories. The softmax activation function used in this layer produces probabilistic results for each emotion. The Adam optimizer was employed to ensure regular weight updates, thereby reducing the loss function and enhancing the accuracy of the model while reducing misclassifications.

Thus, the method presented based on the Inception-v3 architecture achieved the best accuracy level without the need for balancing. In sentiment analysis performed with a dataset of natural disaster images taken from social media, the accuracy values were found to be 89.43% for negative sentiment, 89.61% for positive sentiment, and 88.74% for neutral sentiment. Additionally, the precision values were 90.12% for negative sentiment, 91.56% for positive sentiment, and 89.74% for neutral sentiment. The recall values were 90.07% for negative sentiment, 93.69% for positive sentiment, and 88.94% for neutral sentiment. The F1 score values were 80.69% for negative sentiment, 94.51% for positive sentiment, and 85.77% for neutral sentiment (Table 3).

Although the model had a good learning rate during the training phase, this might not affect the validation data. The validation phase can lead to significant data loss and low validation.[22] Therefore, the same approach was repeated several times before achieving more accurate values for the model's hyperparameters. The confusion matrix for the Inception-v3 model is presented in Figure 3.

Examples of images for positive, negative, and neutral sentiment analysis are presented in Table 4.

## DISCUSSION

In the field of sentiment analysis of natural disaster images, the Inception-v3 model demonstrated superior accuracy, precision, and F1 score compared to other DL models.[23] The primary reasons for its success are that the model enhances computational efficiency through the use of convolutional filters of varying sizes and more effectively captures features within the image.[24] The deployment of Inception-v3 facilitated the comprehension of emotional nuances in disaster-related imagery and showcased the model's efficacy across a diverse array of applications.[25] The results from the study indicating that Inception-v3 performed exceptionally well in sentiment analysis of natural disaster images align with several other studies in the literature. For instance, Yu et al. reported that Inception-v3 achieved an accuracy of 85.13% and an area under curve (AUC) of 0.91 in a diagnostic model for breast ultrasound images.[23] Similarly, Wu et al. found that Inception-v3 attained the

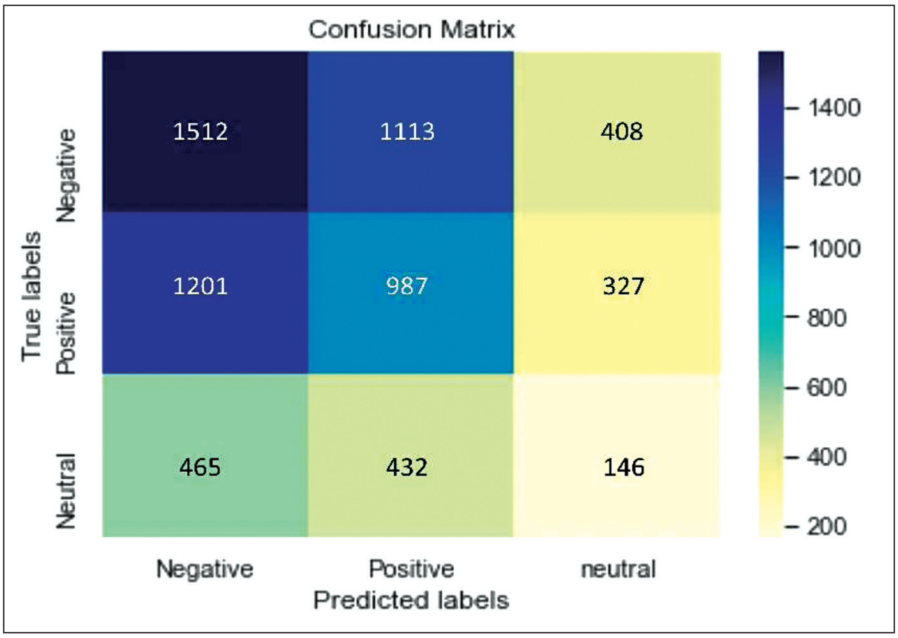


**FIGURE 3:** Confusion matrix of the Inception v-3 architecture.

**TABLE 4:** Examples of images for positive, negative, and neutral sentiment analysis.

| Sentiment polarities | Image |
|---|---|
| Positive |  |
| Neutral |  |
| Negative |  |

highest classification accuracy of 97.57% in differentiating glioma from encephalitis using MR-based DL.[26] Moreover, Mkhatshwa et al. highlighted that Inception-v3 consistently delivered superior performance across various datasets, emphasizing its effectiveness in classification tasks.[27] These studies collectively support the notion that Inception-v3 is a robust DL model capable of achieving high accuracy and performance metrics in diverse applications.

Furthermore, the results obtained in classifying images using Inception-v3 and the work of Saleh et al. in detecting retinal disorders also underscore the model's efficacy in classification tasks.[28] Additionally, the study by Fang et al. on ultrasound image diagnosis and the work of Xiao et al. on breast tumor discrimination further reinforce the superior performance of Inception-v3 in achieving high accuracy and precision values.[29,30] In summary, the consistent success of Inception-v3 across various studies in different domains, including medical imaging, disease classification, and sentiment analysis, highlights its versatility and effectiveness as a DL model. The compatibility of the results with existing literature underscores the reliability and robustness of Inception-v3 in delivering accurate and precise results in classification tasks.

The methodology and approaches used in the study, such as transfer learning, early fusion, Adam optimizer, softmax activation function, and hyperparameter tuning, are well-supported by existing literature. Several studies have demonstrated the effectiveness of these techniques in enhancing the performance of DL models, including Inception-v3, across various domains. Transfer learning has been widely acknowledged for its ability to leverage pre-trained models like Inception-v3 to improve classification accuracy in tasks such as disease detection, histopathology image classification, and sentiment analysis.[31] It allows models to benefit from knowledge gained during training on large datasets, enhancing performance on new tasks with limited data. Moreover, early fusion has shown promise in combining visual and textual features to improve sentiment classification accuracy.[24] This approach aligns with the study's emphasis on early fusion to enhance sentiment analysis. The Adam optimizer and softmax activation function have been recognized for optimizing model training and improving convergence speed.[32] These techniques contribute to efficient training and enhanced performance in classification tasks. Additionally, hyperparameter tuning is crucial for achieving higher accuracy and consistency in model predictions.[33] Iterative adjustments play a crucial role in fine-tuning the model for optimal performance. The methodology and approaches employed in the study, including transfer learning, early fusion, optimizer selection, activation function choice, and hyperparameter tuning, are well-founded in the literature. These techniques have been widely recognized for their effectiveness in enhancing the performance of DL models like Inception-v3, supporting the reliability and validity of the study's methodology.

The performance metrics of DL models, particularly highlighted by the exceptional results of Inception-v3 with 89.4% accuracy for negative sentiment, 89.6% for positive sentiment, and 88.7% for neutral sentiment accuracy, are consistently emphasized in various studies in the literature. Khudaier and Radhi achieved high accuracy, precision, recall, and F1 score values of 0.9455, 0.9465, 0.9455, and 0.9456, respectively, in binary classification tasks using CNN architecture.[34] Similarly, Sukegawa et al. demonstrated high accuracy and AUC values in DL classification tasks related to oral exfoliative cytology.[35] These results indicate that when appropriately configured and optimized, DL models can achieve high accuracy and performance metrics across various domains. The utilization of advanced techniques such as transfer learning, hyperparameter tuning, and optimizer selection, as seen in studies focusing on Inception-v3, plays a critical role in enhancing the effectiveness and reliability of DL models in sentiment analysis and classification tasks. Therefore, the results regarding the performance metrics of Inception-v3 in sentiment analysis align with the broader trends observed in the literature, showcasing the potential of DL models to deliver accurate and reliable results in diverse applications.

The use of the Inception-v3 model for sentiment analysis of natural disaster images carries significant practical implications for disaster management and crisis communication. The utilization of the Inception-v3 model in sentiment analysis of natural disaster images has various practical applications in disaster management, crisis communication, and community engagement. Conducting sentiment analysis using DL helps stakeholders understand public emotional states, improve intervention strategies, and enhance resilience against disasters.

The fact that the data was collected in 2021 and the accessible dataset only covers four social media platforms constitutes a limitation in our study. Due to the limited capabilities of our current computer, we have worked with a restricted number of data samples. Future studies should aim to improve the model performance by using a larger and more diverse dataset. Additionally, exploring transfer learning techniques more comprehensively and investigating the effectiveness of different transfer strategies could potentially enhance the model accuracy.

## CONCLUSION

In this study, the performance of DL models in visual sentiment analysis of images related to natural disasters was evaluated, demonstrating the effectiveness of pre-trained models like Inception-v3 in recognizing and classifying emotional states. Visual sentiment analysis plays a crucial role in disaster management and emergency response processes. Therefore, data obtained during disasters can significantly contribute to providing psychological support, directing resources, assessing disaster impacts, determining community emotional well-being, and optimizing relief efforts.

Future studies should focus on enhancing the performance of DL models by using larger and more diverse datasets. Additionally, further investigation into transfer learning techniques and exploring the effectiveness of different transfer strategies could improve the accuracy and overall performance of emotion recognition tasks. Such research endeavors can encourage more effective utilization of DL models in managing emotional content-related data during disasters and emergency response interventions.

In conclusion, it is evident that data obtained through visual sentiment analysis can play a critical role in disaster management and emergency response processes, highlighting a significant need for research in this field. Studies in this direction are expected to contribute to developing new approaches in crisis communication and understanding and managing the impacts of disasters.

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***Conflict of Interest***

*No conflicts of interest between the authors and / or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.*

***Authorship Contributions***

***Idea/Concept:*** *Gülcan Demir, Gözde Özsezer;* ***Design:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***Control/Supervision:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***Data Collection and/or Processing:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***Analysis and/or Interpretation:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***Literature Review:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***Writing the Article:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***Critical Review:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak;* ***References and Fundings:*** *Gülcan Demir, Gözde Özsezer, Cüneyt Çalışkan, Hüseyin Koçak.*

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