

Explainable Event Recognition

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The literature shows outstanding capabilities for CNNs in event recognition in images. However, fewer attempts are made to analyze the potential causes behind the decisions of the models and exploring whether the predictions are based on event-salient objects/regions? To explore this important aspect of event recognition, in this work, we propose an explainable event recognition framework relying on Grad-CAM and an Xception architecture-based CNN model. Experiments are conducted on three large-scale datasets covering a diversified set of natural disasters, social, and sports events. Overall, the model showed outstanding generalization capabilities obtaining overall F1-scores of 0.91, 0.94, and 0.97 on natural disasters, social, and sports events, respectively. Moreover, for subjective analysis of activation maps generated through Grad-CAM for the predicted samples of the model, a crowd-sourcing study is conducted to analyze whether the model's predictions are based on event-related objects/regions or not? The results of the study indicate that 78%, 84%, and 78% of the model decisions on natural disasters, sports, and social events datasets, respectively, are based on event-related objects/regions.

Additional Key Words and Phrases: Event Recognition, Grad-CAM, Explainability, Interpretation, Convolutional Neural Networks, Natural Disasters, Social Events, Sports Events, Multimedia Indexing and Retrieval

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1 INTRODUCTION

Event recognition in multimedia content (i.e., videos, images, sound tapes, and textual information) has been widely explored in the literature [1]. Several interesting definitions and aspects of events have emerged as part of the efforts in different application domains. The definition of an event largely depends on the nature of the application and the type of content to be analyzed. For instance, in the complex videos, an event can be defined through interactions of multiple objects or/and human actions in scenes with various types of backgrounds [12]. In audio tapes, events depict

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the occurrence of a certain sound pattern [9]. In images, on the other hand, events are represented and differentiated through the presence of certain objects and scenes [1].

A vast majority of the literature aims at event recognition in images where mostly the focus remained on the detection and recognition of certain objects and background information. For instance, in [23], object and scene-level features extracted through individual Convolutional Neural Networks (CNNs), pre-trained on ImageNet [11] and Places [27] datasets, are combined for event recognition. However, all the objects and scenes in an image do not necessarily belong to an underlying event. In fact, there are certain objects and scenes that define and differentiate events. These objects and scenes may lie at any location covering a large or a smaller portion of an image, and are not necessarily be the most prominent parts of the image [3, 17].

Despite such challenges, Deep Learning (DL) models have shown outstanding generalization capabilities in event recognition. The average performance of state-of-the-art methods in terms of average accuracy on widespread datasets, such as *culture*, *social*, *sports*, and *natural disasters* events datasets are in the range of 87%, 70%, 85%, and 68%, respectively [1]. However, the end-to-end learning mechanism of DL models without adequate explanation of the predictions leads to several questions, such as *which parts (i.e., objects and scenes) of an image contribute more to the prediction of the model? are these parts/regions of the images contain event-related objects and scenes? Do all the decisions of the models are based on event-salient objects/regions? Do they make sense to humans?*

In this work, we aim to answer these questions by extending the concept of explainability to event recognition. To this aim, we propose an explainable event recognition framework relying on Gradient-weighted Class Activation Mapping (Grad-CAM) and a CNN architecture. Moreover, the experiments are conducted on three different datasets covering social, sports, and natural disaster events. We believe such a detailed analysis of a diversified set of events will provide a baseline for future work in the domain.

The main contributions of the work can be summarized as follows:

- (1) We extend the concept of explainability to event recognition by adopting explainability methods for a CNN-based event recognition framework.
- (2) We also conduct a crowd-sourcing study to analyze whether the model's predictions are made on event salient objects/regions or not? The study will allow us to analyze how much the models consider event-salient objects/regions in prediction?
- (3) Through an extensive experiments on three different datasets, we aim to answer the following research questions:
 - (a) Which parts (i.e., objects and scenes) of an image contribute more to the prediction of the model?
 - (b) Are these parts of the images contain event-related objects and scenes?
 - (c) Are all the predictions of the model based on event salient objects and regions?
 - (d) Do they make sense for humans?

The rest of the paper is organized as follows. Section 2 provides an overview of literature on event recognition. Section 3 describes the proposed framework. Section 4 summarizes the characteristics and statistics of the datasets used for the experimentation. Section 5 reports the experimental results and key lessons learned. Finally, Section 6 provides some concluding remarks.

2 RELATED WORK

The literature explores different aspects of event recognition in images. For instance, several types of events, such as social [2], cultural [8], political [7], sports [13], and natural disaster events [19], are reported in the literature. From the implementation point of view, different strategies have been adopted relying on both visual and metadata information whenever available. Though the

additional information has been proved effective in several studies, the main focus remained on visual content mostly relying on DL algorithms [1]. Moreover, DL techniques are mostly employed in three different ways either (i) fine-tuning existing pre-trained models, (ii) training or re-training a DL model, and (iii) extracting features with pre-trained models. For instance, Liu et al. [14] fine-tuned two pre-trained models namely VggNet [21] and GoogLeNet [22] on a cultural events dataset. In [16], a CNN model composed of three training and pooling, and two fully connected layers is trained on image regions extracted from cultural events images. In [4], multiple deep models are employed for feature extraction from event-related images.

In visual content-based approaches, the focus remained on objects and scenes (i.e., backgrounds), as a result, several interesting event recognition frameworks, employing object and scene-level features both individually and jointly, are proposed. For instance, Wang et al. [24] combined object and scene-level features extracted through DL models in three different ways using initialization, knowledge, and data-based transfer learning. Similarly, in [25] CNN models pre-trained on objects [11] and scenes datasets [27] are combined in late and early fusion. However, events are represented and differentiated by certain objects and scenes, which are not necessarily be the most prominent parts of an event-related image. This hypothesis is proved by Rosani et al. [17] through a game-based crowdsourcing approach where a large population was asked to highlight/mask the image parts representing an underlying event.

Despite the challenges in the identification/extraction of the event-related objects in an image, end-to-end DL methods have shown outstanding performance. However, the literature is still missing a detailed analysis of what kind of image parts contribute more to the decisions of these models. In this work, we aim to explore the causes behind the predictions made by these models and analyze whether the decisions make sense to humans or not.

3 METHODOLOGY

Figure 1 provides the block diagram of the proposed methodology. The proposed framework for explainable event recognition is composed of two main components. The first component is consisted of fine-tuning a pre-trained CNN model while the other component is based on the Grad-CAM, which generates the activation maps of the images processed by the CNN model. Our CNN model is based on a state-of-the-art architecture namely Xception [10], pre-trained on a large-scale object recognition dataset known as ImageNet [18]. In the next subsection, we provide details of each component of the framework.

3.1 Fine-tuning the Model

The Xception architecture is mainly based on the decoupling hypothesis of mapping cross-channel and spatial correlations. In other words, spatial convolution is performed on each input channel independently. Subsequently, pointwise (i.e., 1x1) convolutional layers are used to project the output of the depthwise convolution. In total, the network consists of 36 convolutional layers, which are structured into 14 modules. All the modules have linear residual connections.

In this work, we fine-tuned a pre-trained version of the model trained on ImageNet dataset [18]. ImageNet is a large-scale object recognition dataset composed of 1000 classes. Fine-tuning brings several advantages. On one side, it reduces training time and computational resources. On the other hand, improves the performance on smaller dataset lacking a sufficient number of training samples. The parameters used in fine-tuning the model are detailed in Section 5.

3.2 Grad-CAM Visualization

In this work, for heatmap visualization, we rely on Gradient-weighted Class Activation Mapping (Grad-CAM) algorithm [20], which is a modified version of CAM [26]. CAM allows identifying the

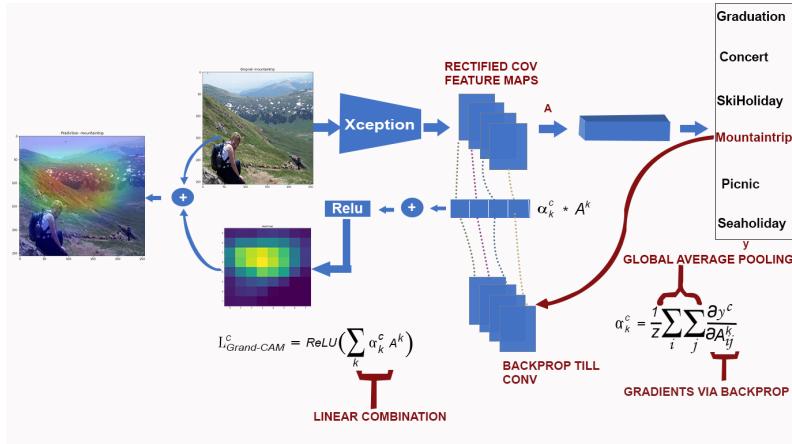


Fig. 1. Block diagram of the proposed methodology.

salient (i.e., discriminative) objects/regions of an image provided to a CNN model by computing class activation maps. The algorithm assigns an importance score to every region by computing a weighted combination of the activations. To this aim, all the fully connected layers from the model are replaced with a global average pooling layer, which helps to avoid over-fitting. The average pooling layer is then followed by a classification (i.e., soft-max) layer.

Grad-CAM extends CAM by generalizing the concept to general CNN architectures by utilizing gradient information in assigning weights to the feature maps. To be more specific the gradient of the loss w.r.t. the last convolutional layer is used to determine the weights.

4 DATASETS

In the literature, three different types of events, including social, sports, and natural disaster events, are explored. In this work, we evaluate the proposed methodology on three different datasets, namely (i) social events dataset, (ii) sports event dataset, (iii) and natural disasters dataset. The basic motivation behind the evaluation of the proposed work on these datasets is to analyze how DL models respond to different types of events covering diversified visual content. In the next subsections, we provide a detailed description of the datasets.

4.1 Social Events Dataset

Social events are among the most commonly used events in the literature [1]. Several datasets, such as USED [2] and EiMM [15] covering different types of social events, such as wedding, graduation, holiday trips, etc., are publicly available for research purposes. In this work, experiments are conducted on the USED dataset. The dataset is provided into two subsets one containing 6 different types of social events while the other cover images from 8 types of events. We consider the 6 events including *concert*, *graduation*, *mountain trip*, *picnic*, *sea holiday*, and *ski holiday*. Some sample images from the dataset are provided in Figure 2.

4.2 Sports Events Dataset

Sports events are also widely explored in the literature. To this aim, mostly UIUC Sports Events Dataset [13] and EiMM datasets [15] have been used. The UIUC sports events dataset is composed of 8 events including *rowing*, *badminton*, *polo*, *bocce*, *snowboarding*, *croquet*, *sailing*, and *rock climbing*. Besides the class labels, the images are also categorized in terms of difficulty level and the distance

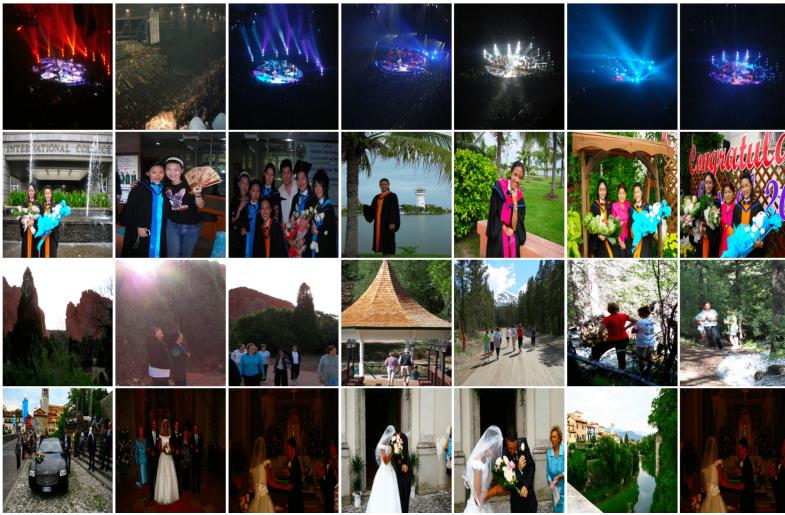


Fig. 2. Sample images from the social events dataset.

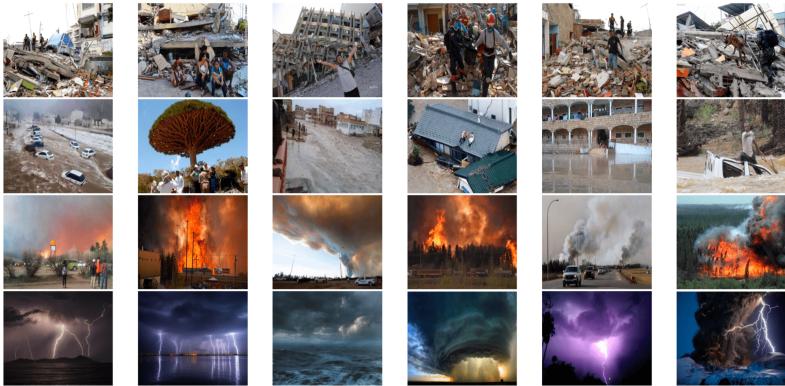


Fig. 3. Some sample images from natural disaster dataset.

of object and for-grounds. Two different difficulty levels, namely (i) easy, (ii) medium are defined on the basis of annotators' judgment. Both the training and test provide equal contribution from each category of images.

On the other hand, the EiMM sports dataset contains images from 9 different types of sports events, namely *baseball*, *basketball*, *bike*, *cycling*, *formula 1*, *golf*, *hockey*, *rowing*, *skating*, and *swimming*. All the images are downloaded from Picasa Web Album service. The annotation is provided at two different levels including events and sub-events labels covering two different tasks, namely (i) event recognition/classification, and (ii) sub-event detection in an image. In this work, we considered the event classification task only. We note that in this work EiMM data is used for the experiments. Figure 4 provides some sample images from the dataset.

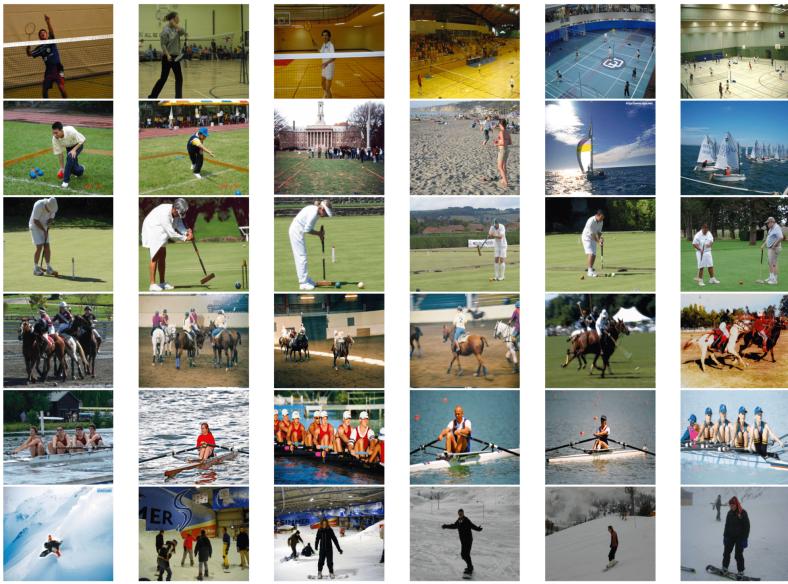


Fig. 4. Some sample images from sports events.

4.3 Natural Disaster Events Dataset

Natural disaster analysis is relatively a new domain and still lacks a large-scale benchmark dataset. In this work, we utilize a subset of the self-collected dataset for our earlier work on natural disaster analysis [5, 6]. The dataset is composed of 4 common natural disasters, namely *earthquakes*, *floods*, *thunderstorms*, and *wildfires*. Compared to social and sports events, natural disaster-related images provide more diversified contents, and thus more challenging. Figure 3 provides some sample images from the dataset.

5 EXPERIMENTS AND RESULTS

In this section, we provide details of the experimental setup, conducted experiments, and results.

5.1 Experimental Setup

We made several changes for fine-tuning an existing pre-trained model on our datasets. As a first step, a normalization layer is used to adjust the input in the range of $(-1., +1.)$ as required for using the pre-trained model's weights. Moreover, a very low learning rate (i.e., $1e-5$) is used for the lower layers of the models to learn slowly compared to the newly added layers. The newly added layers include a global averaging pooling layer and a regular densely connected layer. Moreover, activation maps are generated from the last convolutional layer namely “block14_sepconv2_act”. Moreover, Adam optimizer is used for 10 epochs with a batch size of 120.

5.2 Experimental Results

5.2.1 Natural Disasters Events. Table 1 provides the experimental results of the model on the natural disaster dataset in terms of precision, recall, and F1-score. As can be seen in the table, overall good results are obtained with a weighted average F1-score of 0.91%.

The high scores on each type of natural disaster show the generalization capabilities of the model. However, it would be interesting to see if the model's decision is based on event-related objects or

Table 1. Experimental results on natural disasters events in terms of precision, recall, and F1-score.

Class	Precision	Recall	F1 Score
Earthquake	0.91	0.92	0.91
Floods	0.84	0.94	0.89
Thunder Storm	0.89	0.83	0.86
Wildfires	0.98	0.94	0.96
Weighted Average	0.91	0.91	0.91

Table 2. Experimental results on sports events in terms of precision, recall, and F1-score.

Class	Precision	Recall	F1 Score
Baseball	0.94	0.98	0.96
Basketball	0.96	0.95	0.95
Bike	0.94	0.91	0.93
Cycling	1.0	0.89	0.94
F1 Race	0.88	0.98	0.93
Golf	0.98	0.99	0.98
Hockey	0.96	0.99	0.98
Rowing	0.99	0.99	0.99
Skating	0.97	0.99	0.98
Swimming	0.99	0.99	0.99
Weighted Average	0.97	0.97	0.97

not? and are the objects identified by the model as distinguishing features for the classes make sense to humans or not? To answer these questions, as a sample, we provide the activation maps generated by the Grad-CAM algorithm in Figure 5.

As can be seen in the figure, the image regions/objects used by the model (as highlighted in the figures) are relevant to the underlying events. For instance, in the earthquake samples shown in Figure 5(a) only the broken parts of the buildings are highlighted in the activation maps. Similarly, in wildfires images, only the regions containing fire or smoke are highlighted in the activation maps. The same is the case with the other samples from the dataset.

It is also important to analyze the activation maps of the misclassified samples. This will help us in understanding the causes of the misclassification. In Figure 6, we provide some misclassified samples from different classes. The activation maps of the misclassified samples help in analyzing the potential causes of the model failure. Apparently, the misclassification seems due to the similar type of texture/content of the images with the images from the misclassified classes. For instance, as can be seen in Figure 6(a), in the first two images (from the left) the model focuses on the clouds in the sky, which is one of the salient features of the thunderstorm class, instead of the broken house. One of the potential reasons could be the less or un-noticeable damage to the house as the building seems undamaged in the second image. Thus, despite the failure in correctly predicting the events, the decision of the model makes sense to human observers.

5.2.2 Sports Events. Table 2 provides the experimental results of the model on the sports events dataset. As can be seen, the overall weighted average as well as precision, recall, and F1-score on the individual classes is very high.

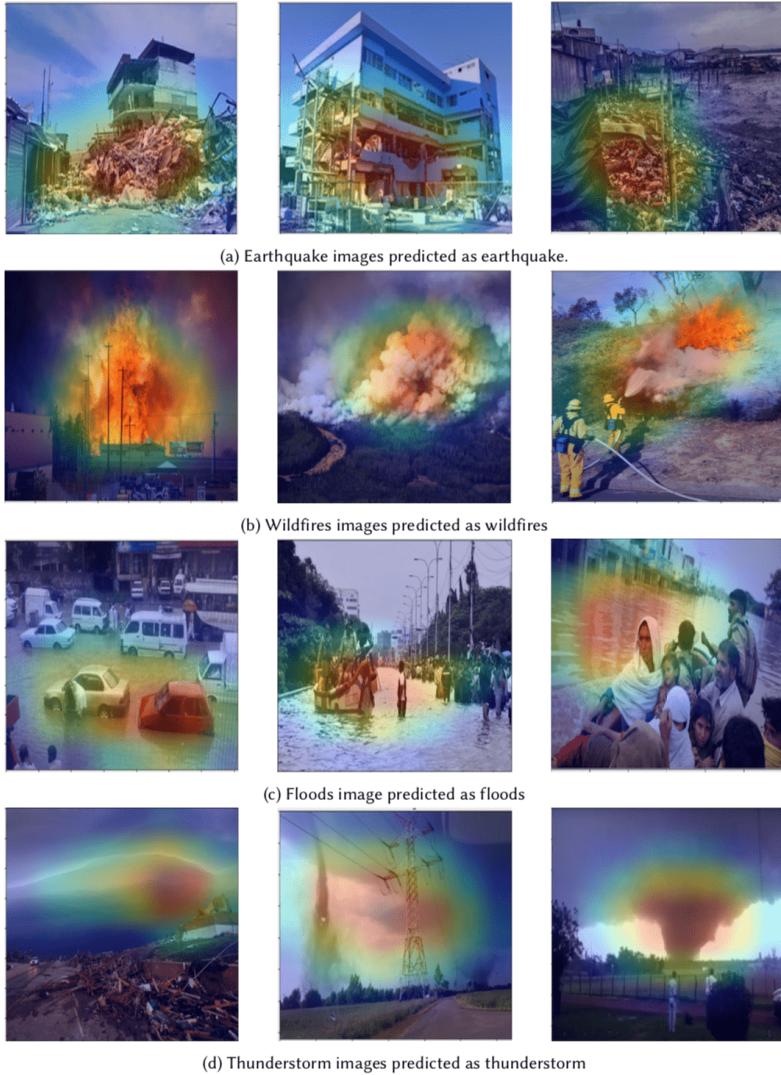


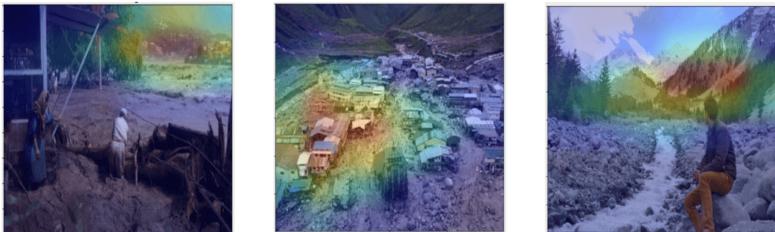
Fig. 5. Activation maps generated via Grad-CAM of correctly classified samples from natural disaster events dataset. As can be seen, in most of the cases, the model decisions are made on correct objects/regions.

Similar to natural disaster events, we also provide some sample activation maps generated through Grad-CAM in Figure 7 to show the key objects and image regions influencing the model's decision. Similar to natural disaster events, in most cases the model's decisions are based on relevant objects. For instance, as can be seen in Figure 7(a), basketball-related images are classified on the basketball goods, such as the ball and basket. Similarly, the bike race events are classified on the presence of bike and rider. The same trend is also observed in the other events.

The activation maps of the misclassified samples from the sports events dataset are provided in Figure 8. As can also be seen in the figure, most of the misclassified samples lack event salient objects, such as bike for bike racing, cycle for cycling, etc. Thus the decisions seem to have been



(a) Earthquake images misclassified as thunderstorms, thunder storm, and floods (left to right). As can be seen in the first two images from the left, the model focuses on the clouds in the sky, which is one of the salient features of the thunderstorm class.



(b) Floods images are misclassified as thunder storm, earthquakes, and wildfires, respectively (left to right). Flood-related images containing broken houses and forests are the potential visual cues causing the misclassification as earthquakes and wildfires, respectively.



(c) Thunderstorm images are misclassified as earthquakes, wildfires, and floods, respectively (left to right). The broken house, the red color in the sky, and the mud (i.e., bare land/mountains) could be the potential causes of the misclassification of images as earthquakes, wildfires, and floods, respectively.

Fig. 6. Wrongly predicted samples from natural disasters events Dataset. *The misclassification is mostly due to visual similarities with the classes.*

taken on the basis of secondary i.e, less relevant objects, which is one of the potential causes of the misclassification.

5.2.3 Social Events. Table 3 provides the experimental results on the social events dataset. Similar to the other datasets, the model has shown outstanding recognition capabilities on the dataset by obtaining an overall weighted average F1-score of 0.94. The high score on the dataset shows the better performance of the model in differentiating among the social events. However, it will be interesting to see whether the predictions made on the relevant object or not?

Figure 9 provides some sample activation maps generated on social events images. Similar to natural disasters and sports events, in most cases, the predictions are made on the basis of event-related objects. For instance, as can also be seen in Figure 9(a), concerts images are classified on the presence of musical instruments and lighting. Similarly, the graduation images are classified on the basis of the graduation gown and cap.

Figure 10 provides some misclassified samples from the social events dataset to analyze the potential causes of the model's failure. As can also be seen in Figure 10(a), the concert images

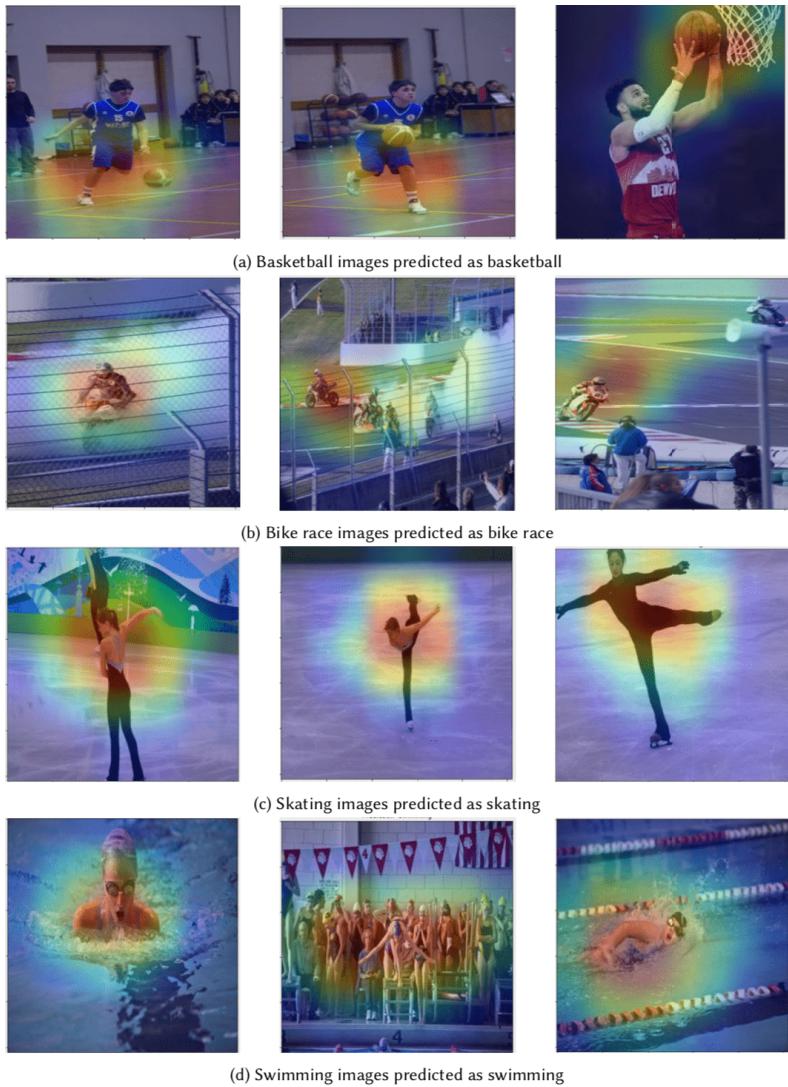


Fig. 7. Activation maps generated via Grad-CAM of correctly classified samples from sports events dataset. As can be seen, the model decisions are made on correct objects/regions of the images.

are mostly misclassified as graduation mainly due to the presence of the singer. We found several misclassified images where a singer in front of a mic has been highlighted as the object influencing the model's decision. Similarly, picnic images are mostly confused with sea-holiday, mountain trip, and ski-holiday due to the common visual cues. The same is the case with the other classes.

5.3 Subjective Analysis through Crowd-sourcing

In the subjective analysis, we aim to manually analyze the activation maps in a crowd-sourcing study to verify whether the decision of the ML model is based on event-related objects/regions or not? To this aim, a group of Masters students was asked to manually check the activation maps



Fig. 8. Wrongly predicted samples from sports events Dataset. *The misclassification is mostly due to visual similarities with the classes.*

Table 3. Experimental results on social events in terms of precision, recall, and F1-score.

Class	Precision	Recall	F1 Score
Concert	0.93	0.94	0.93
Graduation	0.96	0.92	0.94
Mountaintrip	0.91	0.95	0.93
Picnic	0.94	0.92	0.93
Sea Holiday	0.95	0.91	0.93
Ski Holiday	0.93	0.98	0.95
Weighted Average	0.94	0.94	0.94

of correctly predicted samples generated through Grad-CAM as shown in Figure 5, Figure 7, and Figure 9, and decide if the objects/regions on the basis of which the predictions are made belong to the underlying event or not. Each sample is manually analyzed by at least three different persons, and the final decision is made on the majority votes. The participants of the study were asked to label the samples either as 1 or 0, where label 1 represents that the prediction is made on the basis

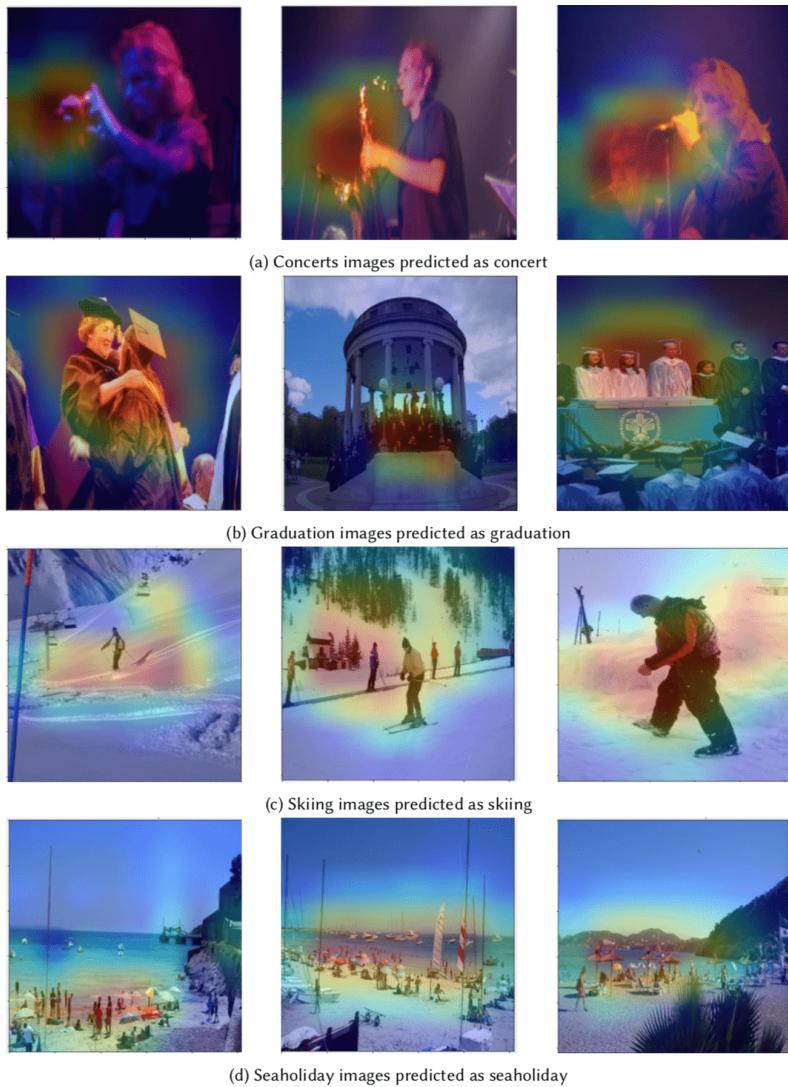


Fig. 9. Activation maps generated via Grad-CAM of correctly classified samples from social events dataset. As can be seen, the model decisions are made on correct objects/regions of the images.

of event-related objects/regions. Once all the samples are labeled, we computed a score by dividing the number of samples labeled as 1 divided by the total number of the samples. We termed this score as the accuracy of the model in identifying and making a decision on event-related objects/regions.

Table 4, Figure 5, and Figure 6 show the scores obtained during the study on natural disasters, social, and sports events, respectively. Overall good scores are obtained on each dataset with a highest score of .84 on social events dataset. One of the possible reasons of the higher score on the dataset could be linked with the high inter class variation.

As far as the scores on the individual classes are concerned, the highest scores are obtained for wildfires and earthquake images while lowest scores are obtained on floods and thunder storm.



(a) Concert images mis-classified as graduation due to the presence of the singer.



(b) Picnic images are misclassified as sea-holiday, mountain trip, and sea-holiday, respectively (left to right). These images share common visual content with the misclassified classes.



(c) Mountain trip images are misclassified as sea-holiday, picnic, and ski-holiday, respectively (Left to right). These images share common visual content with the misclassified classes.

Fig. 10. Wrongly classified samples from social events dataset. *The misclassification is mostly due to visual similarities with the confused classes.*

Table 4. Subjective analysis results on the natural disasters events in terms of accuracy.

Class	Accuracy
Earthquake	0.80
Floods	0.76
Thunder Storm	0.77
Wildfires	0.81
Weighted Average	0.78

Similarly, in social and sports events, the highest scores are obtained on graduation and hockey-related images, respectively. On the other hand, lowest scores in these datasets are obtained on sea holiday and F1 race. The lower scores could be linked to the complexity of these classes, however, interestingly the recall on these classes, as can be seen in Table 1, 3, and Table 2, are high. Since in the subjective analysis we considered the correctly predicted samples only, one of the potential reasons could be the correct prediction of complex images in these classes where the decisions are made on secondary objects due to absence of event-related objects.

Table 5. Subjective analysis results on social events in terms of accuracy.

Class	Accuracy	Class	Accuracy
Concert	0.86	Graduation	0.88
Mountaintrip	0.82	Picnic	0.77
Sea Holiday	0.58	Ski Holiday	0.77
Weighted Average	0.78	-	-

Table 6. Subjective analysis results on sports events in terms of accuracy.

Class	Accuracy	Class	Accuracy
Baseball	0.90	Basketball	0.93
Bike	0.75	Cycling	0.78
F1 Race	0.53	Golf	0.64
Hockey	0.98	Rowing	0.89
Skating	0.96	Swimming	0.82
Weighted Average	0.84	-	-

5.4 Lessons Learned

The key lesson learned from the work can be summarized as follows.

- Event recognition in single images is a challenging task compared to object recognition as event-related images generally include multiple objects and scene-level details, which are not necessarily all related to the underlying event.
- The model has shown outstanding capabilities in predicting complex events.
- The concept of explanation of the ML model by generating activation maps from the final convolutional layer allows to analyze whether the model's decisions make sense to a human observer or not.
- The activation maps generated via Grad-CAM in this work show that in the majority of cases the model's decisions are based on event-related objects.
- In most of the cases the misclassification is due to visual similarities with the confused classes or the absence of event salient objects.
- The subjective analysis indicates that generally, the model performed well in identifying event salient objects and image regions. However, the results show a significant gap, which should ideally be near to 100% (i.e., ideally all the decisions of the models should be based on event-salient objects). The gap indicates the need for more efforts on event-salient aspects of event recognition.

6 CONCLUSION

In this work, we presented an explainable event recognition solution to analyze whether the prediction of the model is based on event-related objects/regions or not. To this aim, the Grad-CAM algorithm is employed to generate activation maps of the images used by a CNN model. Moreover, to evaluate the performance of the model in terms of correctly identifying event-related objects/regions, a subjective study is conducted where participants were asked to analyze whether the decision is made on event-related objects or not? Overall, the model showed better results in terms of making decisions/predictions on event-related objects. However, ideally it should be near to 100%, and the gap indicates more efforts are required to explore this aspect of event recognition.

REFERENCES

- [1] Kashif Ahmad and Nicola Conci. 2019. How deep features have improved event recognition in multimedia: A survey. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)* 15, 2 (2019), 1–27.
- [2] Kashif Ahmad, Nicola Conci, Giulia Boato, and Francesco GB De Natale. 2016. Used: a large-scale social event detection dataset. In *Proceedings of the 7th International Conference on Multimedia Systems*. 1–6.
- [3] Kashif Ahmad, Nicola Conci, and Francesco GB De Natale. 2018. A saliency-based approach to event recognition. *Signal Processing: Image Communication* 60 (2018), 42–51.
- [4] Kashif Ahmad, Mohamed Lamine Mekhalfi, Nicola Conci, Giulia Boato, Farid Melgani, and Francesco GB De Natale. 2017. A pool of deep models for event recognition. In *2017 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2886–2890.
- [5] Kashif Ahmad, Konstantin Pogorelov, Michael Riegler, Nicola Conci, and Pal Halvorsen. 2019. Social media and satellites: Disaster event detection, linking and summarization. *Multimedia Tools and Applications* 78, 3 (2019), 2837–2875.
- [6] Kashif Ahmad, Amir Sohail, Nicola Conci, and Francesco De Natale. 2018. A comparative study of global and deep features for the analysis of user-generated natural disaster related images. In *2018 IEEE 13th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)*. IEEE, 1–5.
- [7] Unaiza Ahsan, Chen Sun, James Hays, and Irfan Essa. 2017. Complex event recognition from images with few training examples. In *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 669–678.
- [8] Xavier Baro, Jordi Gonzalez, Junior Fabian, Miguel A Bautista, Marc Oliu, Hugo Jair Escalante, Isabelle Guyon, and Sergio Escalera. 2015. Chalearn looking at people 2015 challenges: Action spotting and cultural event recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 1–9.
- [9] S Chandrakala, M Venkatraman, N Shreyas, and SL Jayalakshmi. 2021. Multi-view representation for sound event recognition. *Signal, Image and Video Processing* (2021), 1–9.
- [10] François Fleuret. 2017. Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 1251–1258.
- [11] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 248–255.
- [12] Chuang Gan, Naiyan Wang, Yi Yang, Dit-Yan Yeung, and Alex G Hauptmann. 2015. Devnet: A deep event network for multimedia event detection and evidence recounting. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2568–2577.
- [13] Li-Jia Li and Li Fei-Fei. 2007. What, where and who? classifying events by scene and object recognition. In *2007 IEEE 11th international conference on computer vision*. IEEE, 1–8.
- [14] Mengyi Liu, Xin Liu, Yan Li, Xilin Chen, Alexander G Hauptmann, and Shiguang Shan. 2015. Exploiting feature hierarchies with convolutional neural networks for cultural event recognition. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*. 32–37.
- [15] Riccardo Mattivi, Jasper Uijlings, Francesco GB De Natale, and Nicu Sebe. 2011. Exploitation of time constraints for (sub-) event recognition. In *Proceedings of the 2011 joint ACM workshop on Modeling and representing events*. 7–12.
- [16] Sungheon Park and Nojun Kwak. 2015. Cultural event recognition by subregion classification with convolutional neural network. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 45–50.
- [17] Andrea Rosani, Giulia Boato, and Francesco GB De Natale. 2015. Eventmask: A game-based framework for event-saliency identification in images. *IEEE Transactions on Multimedia* 17, 8 (2015), 1359–1371.
- [18] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. 2015. Imagenet large scale visual recognition challenge. *International journal of computer vision* 115, 3 (2015), 211–252.
- [19] Naina Said, Kashif Ahmad, Michael Riegler, Konstantin Pogorelov, Laiq Hassan, Nasir Ahmad, and Nicola Conci. 2019. Natural disasters detection in social media and satellite imagery: a survey. *Multimedia Tools and Applications* 78, 22 (2019), 31267–31302.
- [20] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. 2017. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*. 618–626.
- [21] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).
- [22] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich, et al. 2015. Going deeper with convolutions. *Cvpr*.
- [23] Limin Wang, Zhe Wang, Wenbin Du, and Yu Qiao. 2015. Object-scene convolutional neural networks for event recognition in images. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*. 30–35.

- [24] Limin Wang, Zhe Wang, Yu Qiao, and Luc Van Gool. 2018. Transferring deep object and scene representations for event recognition in still images. *International Journal of Computer Vision* 126, 2 (2018), 390–409.
- [25] Xiu-Shen Wei, Bin-Bin Gao, and Jianxin Wu. 2015. Deep spatial pyramid ensemble for cultural event recognition. In *Proceedings of the IEEE international conference on computer vision workshops*. 38–44.
- [26] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. 2016. Learning deep features for discriminative localization. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2921–2929.
- [27] Bolei Zhou, Agata Lapedriza, Jianxiong Xiao, Antonio Torralba, and Aude Oliva. 2014. Learning deep features for scene recognition using places database. In *Advances in neural information processing systems*. 487–495.