# Exploring the Role of Fear in Human Decision Making

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## ABSTRACT

This study explores the use of Convolutional Neural Networks (CNNs) to classify fear in the context of decision-making. The approach involves developing a CNN model that is trained using hyper-parameter tuning and K-fold cross-validation to accurately classify fear from video footage of participants' facial expressions during an experiment. The videos are presented along with a map to show the location of the participants along the route. The study reports an overall accuracy of 95.05% for fear classification. The results show that the model can successfully predict fear levels in different conditions. For example, the most desolate route with the lowest light levels recorded an overall fear detected at 49.15%, while the safest route with the highest light levels in a densely populated area saw an overall fear detected at 2.69%. These findings demonstrate the potential for using CNNs to classify fear and provide insight into how fear can be taken into consideration for decision-making in realistic scenarios.

## KEYWORDS

Human Decision Making, Emotion Classification, Convolutional Neural Network, Safer Routes Navigation

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## 1 INTRODUCTION

The aim of this academic publication is to explore the concept of utilising the emotion of fear within Artificial Intelligence to facilitate decision-making in realistic scenarios. The inspiration for this idea stems from the comparison between how humans and Artificial Intelligence learn, particularly in the early stages of development. The concept of classical and operant conditioning is loosely applied to machine learning to enable the AI system to receive positive reinforcement for correct classifications and subsequently encourage the behavior [12]. Similarly, the concept of classical conditioning is used to examine the possibility of Artificial Intelligence learning fear and applying it to everyday scenarios to keep the user safe. The AI system is designed to make decisions based on the comprehension that certain actions may result in consequences. One example is in the healthcare industry, where AI is used to identify health conditions. However, there is a risk of wrongly identifying an illness, resulting in unnecessary medication usage. By applying a fear response, the AI system could classify extreme cases with greater certainty due to the higher level of fear associated with such cases, making it less likely to be avoided.

This paper aims to study the application of fear within decision-making by examining relevant research areas. One such area is emotion classification [1], which involves exploring how the classification of emotions can be applied. This can be achieved by investigating studies that use biological readings such as Electroencephalogram (EEG) signals [4] to analyse brain activity when reacting to stimuli or Electrocardiograms (ECG) to analyse the heart rate of a participant, where a higher heart rate indicates a higher level of fear. Alternatively, emotions can be determined through facial expressions, auditory responses (such as detecting fear through distress in a user's voice), or other physical gestures such as shaking, cheering, or emotional responses like crying. These can be used to identify emotions in users. Additionally, research into decision-making within Artificial Intelligence, such as in the healthcare sector, will be used to determine scenarios where fear detection can facilitate decision-making.

The objective of this paper is to present the design and implementation of an Artificial Intelligence system that classifies fear and applies it to decision-making in a realistic scenario. The performance of the Neural Network is assessed against previous emotion classification models, with significant thresholds established. The program's results are analysed, and graphs are produced to evaluate the project's significance and the validity of the data collected from experiments. Overall, the study presents a comprehensive approach to fear classification in Artificial Intelligence and its application in decision-making scenarios.

The proposed scenario in this study is based on the existing concept of digital map applications, such as Google Maps [](Google, 2005), which calculates and presents the fastest route to the user, taking into account factors such as traffic and peak times. However, this study proposes a novel approach by incorporating fear classification to determine the safest route, which is determined to be the least fear-inducing route. Specifically, the proposed study aims to identify routes with different conditions that could potentially result in varying levels of fear, such as an unlit alleyway at night, where light levels are low, versus an open public street in the middle of the day, where light levels are high. By detecting and analysing the levels of fear in these different scenarios, the study aims to identify the safest routes for users. This will be determined using


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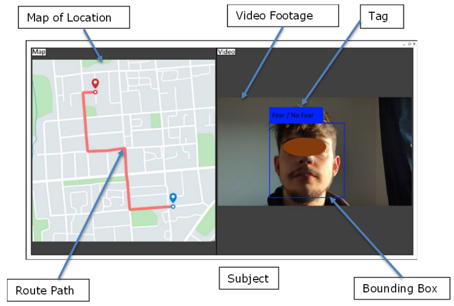


**Figure 1: An illustration of the proposed model for fear detection applied in decision-making.**

the percentage of fear detected from the output of the trained CNN model. An illustration of the application of the proposed approach is presented in Figure 1.

The following sections in this paper are structured as follows: Section 2 presents the review of related works. In Section 3, the methodology used in this work to explore the role of fear in human decision-making is presented, and in Section 4, the experiments and results are reported. This is followed by the conclusion and future work in Section 5.

## 2 RELATED WORK

This section reviews existing solutions where decision-making is largely applied within machine learning, research into the areas which have defined a form of fear or emotion classification, and the techniques that have been applied to achieve significant outcomes. Also, it explores recent case studies looking into the use of human emotion classification applied to everyday tasks.

In the research presented in [2] on the use of Artificial Intelligence (AI) systems for ethical decision-making, concerns are raised regarding the potential lack of oversight in the decision-making process of autonomous systems. The article argues that AI weapons have the potential to make more informed and accurate decisions due to their access to a greater set of resources. However, in the context of the research proposed in this paper, there is a need for incorporating more human-like feelings, e.g. 'fear' within the decision-making process to ensure a more ethical AI. By introducing the concept of fear, the AI system would have a greater awareness of the potential consequences of its decisions, leading to a more objective approach to decision-making. This would ultimately reassure users of the technology that the system is acting ethically and with greater consideration for the safety of friendly personnel and bystanders.

A study on the use of AI in decision-making in the healthcare sector [10], describes the implementation of a Clinical Decision Support System (CDSS) that utilises AI to aid in the diagnosis of medical conditions, such as wrist fractures and cardiovascular disease, by analysing medical images. The study highlights that the CDSS system demonstrated accuracy levels comparable to those of experienced clinicians and is capable of incorporating patient history, such as previous diagnoses of diabetes, into its analysis. However, a limitation of the research is that it does not take into account human sentiments, such as feelings of emotions in its decision making process. Incorporating such sentiments into the CDSS system could enhance the ethical considerations of AI in diagnosing patients. Specifically, incorporating fear could discourage the CDSS system from providing inconclusive or uncertain diagnoses that could lead to incorrect treatment and harm to the patient. Instead, the CDSS system should only provide a diagnosis when there is a high degree of certainty to ensure patient safety. Overall, incorporating fear into the decision-making process of AI in healthcare could enhance the ethical considerations of the technology and ultimately lead to improved patient outcomes.

Another study by [3] explores fear classification using electroencephalogram (EEG) data to train Machine Learning models. The study involved 32 participants and utilised a 4-level classification (No Fear, Low Fear, Medium Fear, and High Fear) and a 2-level binary classification (No Fear, Fear). The processed database from a previous study [9] was used for this research. Results showed that the 4-level classification had a lower accuracy of 68.98% compared to the 2-level classification which had an accuracy of up to 82.26%. The article also employed K-fold cross-validation, which validated the datasets' ability to classify fear. Although the 4-level classification showed potential benefits in identifying the level of fear, the lower accuracy limits its applications. On the other hand, the 2-level classification has significant applications, including decision-making processes. The authors in [11] also used a Convolutional Neural Network (CNN) model in the classification of fear from physiological data obtained using an electrocardiogram (ECG) and electrodermal activity. The work focused on the 2-level binary classification of fear similar to [3]. Although the study in [11] produced reasonable results, their model was tested on a highly imbalanced dataset that required artificial augmentation which limits the generalisation of their work to realistic scenarios. Other works focusing on the study of fear and its impact on decision-making using different case studies predominantly utilise the 2-level binary classification approach [1, 8, 9].

This paper's proposed research is similar to the reviewed studies in that it employs a CNN to classify fear into a 2-level binary system. However, it deviates from the reviewed works by examining the impact of fear on human decision-making through a facial emotion recognition approach. Specifically, the study focuses on the use of digital map applications, such as Google Maps, to provide safer navigation routes in daily life.

## 3 METHODOLOGY

This section describes the methodology proposed in this paper. As mentioned in the review of related works in Section 2, this study makes use of facial image information for facial emotion classification using a trained CNN model. The paper focuses on a binary classification approach used in detecting 'Fear' and 'No Fear' in human faces. The output of the detection is applied to decision-making for better navigational routes recommendation.

### 3.1 Data Pre-processing

To accurately classify fear, a dataset for emotion detection, Facial Expression Recognition 2013 (FER2013) dataset was sourced [5]. To enhance the recognition of fear in facial expressions, the emotion

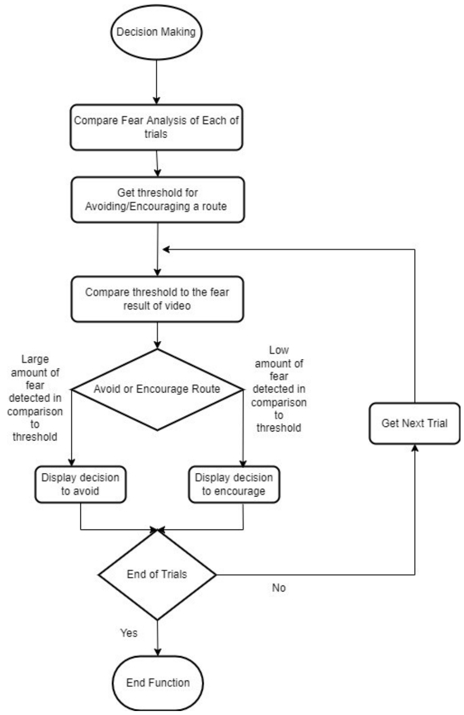


**Figure 2: The process of decision-making from fear detection in video streams.**

classes for happy, angry, disgusted, sad, and surprised were removed. This enabled binary classification of fear, similar to the approach used in prior research studies [1], thus allowing the classification model to learn the concept of fear. The remaining emotion classes in the dataset included Neutral facial expressions denoting 'No Fear', and fearful facial expressions indicating 'Fear'. The remaining dataset comprised 5064 images for Fear class and 5711 images for No Fear class of which had been pre-processed to be grayscale images of which were scaled to be 48 x 48 pixels.

## 3.2 CNN model for Fear Detection

A deep Convolutional Neural Network (CNN) was employed to classify fear using the FER2013. The network is composed of an Input layer comprising 2305 Neurons, which is used to classify images. The CNN contains three hidden convolutional layers and an additional output layer for the final classification. This architecture allows for the image to be decomposed into smaller components, thus enhancing classification accuracy. Hyper-parameter tuning was used to optimise the performance of the CNN model. Optimal values for the hidden layers, dropout, learning rate, and optimal number of epochs were determined.

After identifying the optimal parameters and number of epochs, the model was trained and resulted in an accuracy of 95.05%. This level of accuracy is noteworthy in the field of fear classification.

## 3.3 Decision Making from Fear Detection

The proposed approach involves an analysis of each frame of the Video Capture obtained during the experiment. Specifically, faces identified within each frame are subjected to rescaling and conversion to grayscale, to conform to the input requirements of the classification models. The models are trained to predict whether the detected facial expressions convey "No Fear" or "Fear". The outcome of the prediction is represented as a Tag, which is subsequently associated with the subject's face, along with a Box indicating the location of the detected face within the image. If fear is detected, this information is recorded for subsequent video analysis. At the end of the video, the fear analysis results are compiled into a fear score and reported.

The process of how decision-making is applied to the scenario is illustrated in Figure 2. By analysing all the fear detected across each experiment, this will gain a mean value which is used as a threshold for whether the decision to avoid or encourage a route is chosen (e.g., A route above the threshold showing high levels of fear would be avoided); Therefore, for each trial with fear analysis, there will be a comparison against the threshold and display "Avoid" or "Encouraged" depending on the outcome. The process will continue to iterate through each instance until every trial analysis has been compared, then the function will terminate.

# 4 EXPERIMENT AND RESULTS

The experiments conducted in this work involve recording participants faces along given sets of routes, over different conditions; A concept loosely inspired by Google Maps fastest route [6], with the concept of finding the safest route by analysing the facial expressions of participants along the routes. A decision to avoid or encourage a route would be determined by how much fear had been expressed by the involved participants. The video for the routes were recorded on a Google Pixel 6 mobile device at 1920 x 1080 resolution, where the flash was used when light levels were exceedingly low and a face may not be easily identified. Additionally, the route information was recorded on the same device using Strava [7] to track participants along the route.

The experiment involved two participants recording a front view of their face which would be used to classify fear as well as recording the route taken on Strava; While recording the participants involved walking a given route at a given time of the day, with the participants acting as if it was a casual walk, additionally it was noted that there should be no other interaction of which could be misconstrued as an expression since the information being recorded aims to get a generalisation of a typically regular walk with limited external interaction such as a humorous reaction to the people around them. The given participants involved were made aware of these requirements as well as the details of the experiment, and the application of the results to which the participants provided informed consent before taking part in the experiment.

The conditions in which the experimental data was collected are presented in Table 1. Route data collected is used to visually analyse where fear is most common throughout the trial. The route is plotted against a map from Googles Static Map API, by requesting a path based on the current percent of frames of the total of the video in relation to the amount of latitude and longitude coordinates provided by the GPX information from Strava, this allows for real time tracking between where participants are on the route and the video that is being displayed.

**Table 1: Description of Experimental Conditions**

| Time/Route | Condition | Description |
|---|---|---|
| Time of Day | Morning ( 10:00 am - 12:30pm) | • In the case of "Morning" the aim was to complete the routes at a time of day where the light level was bright enough where vision is best with the theory that morning would produce the "safest" results.<br>• There was a larger leniency between morning time since there was more focus on the given light level at the specified time of day. |
| | Evening (7:30 pm and 8:10 pm) | • The light levels at evening were to be noticeably more reduce as that of morning to represent sunrise and sunset.<br>• In theory due to the slight reduction in vision, could produce more of a fear expression than that of the Morning, although the majority of features within people and objects remain clear. |
| | Night between (9:00 pm and 9:45 pm) | • The light levels are reduced to lowest points of visibility where some points of the route become more invisible by being out the way of street lights.<br>• In theory by visibility reduced to a minimal level, there is more fear being expressed, by in essence fearing the unknown since: objects, people and some streets have unclear features so there is less confidence of "safety" and higher unconscious expressions of fear. |
| Routes | Route 1 | • The fastest route taking an estimated 2 minutes of walking to reach the given destination, the route follows a straight path, and is often not populated with large groups of people, however paths adjacent to the majority of the route lead to more densely populated areas. |
| | Route 2 | • The route takes an estimated time of 3 minutes of walking, initially starting by going through an alley way of which could provoke high levels of fear; However, the alleyway leads into a highly populated street of which contains a variety of shops and eating establishments of which are often opened late at night. Although the alley way would be thought to be fear inducing this may be contradicted by leading to a densely populated area. |
| | Route 3 | • The longest route to the destination taking an estimated time of 6 minutes. The route involves walking along a path which is more out of the way and is, therefore, less populated, there are very few public establishments that can be accessed making it in theory the most likely route to be avoided. Additionally, it is the least lit during the darker hours of the day. |

Decision-making is applied by the overall fear scores detected within the videos, the decision will be made based on the comparison between the scores of each individual routes, routes ranking lower will be decided as "avoid" due to higher levels of fear and routes ranking higher will be decided as "encouraged" to as they present the least fear and is therefore considered safer.

Figure 3 displays the results indicating that the condition with the highest overall fear level was when participant 1 took Route 3 at night, which had the lowest light levels. It is worth mentioning that this condition did not have a third party observing the experiment, which could have led to more natural reactions and contributed to the highest fear levels at night, as anticipated in the study. However, unexpected results were observed during the

**Table 2: Results from the human decision-making model taking into consideration the level of fear detected from all participants in different conditions.**

| Condition | Participant | Time of Day | Route | Detected Fear (%) | Decision |
|---|---|---|---|---|---|
| Condition 1 | Both | Evening | Route 1 | 42.65 | Avoid |
| Condition 2 | Both | Evening | Route 2 | 45.50 | Avoid |
| Condition 3 | Both | Evening | Route 3 | 43.09 | Avoid |
| Condition 4 | Both | Morning | Route 1 | 5.84 | Encouraged |
| Condition 5 | Both | Morning | Route 2 | 22.67 | Avoid |
| Condition 6 | Both | Morning | Route 3 | 11.26 | Encouraged |
| Condition 7 | Both | Night | Route 1 | 21.80 | Avoid |
| Condition 8 | Both | Night | Route 2 | 16.41 | Encouraged |
| Condition 9 | Both | Night | Route 3 | 16.39 | Encouraged |
| Condition 10 | Participant 1 | Evening | Route 1 | 12.37 | Encouraged |
| Condition 11 | Participant 1 | Evening | Route 2 | 7.50 | Encouraged |
| Condition 12 | Participant 1 | Evening | Route 3 | 13.84 | Encouraged |
| Condition 13 | Participant 1 | Morning | Route 1 | 10.56 | Encouraged |
| Condition 14 | Participant 1 | Morning | Route 2 | 2.69 | Encouraged |
| Condition 15 | Participant 1 | Morning | Route 3 | 2.94 | Encouraged |
| Condition 16 | Participant 1 | Night | Route 1 | 23.39 | Avoid |
| Condition 17 | Participant 1 | Night | Route 2 | 29.21 | Avoid |
| Condition 18 | Participant 1 | Night | Route 3 | 49.15 | Avoid |
| Condition 19 | Participant 2 | Evening | Route 1 | 15.67 | Encouraged |
| Condition 20 | Participant 2 | Evening | Route 2 | 25.86 | Avoid |
| Condition 21 | Participant 2 | Evening | Route 3 | 18.26 | Encouraged |
| Condition 22 | Participant 2 | Morning | Route 1 | 13.19 | Encouraged |
| Condition 23 | Participant 2 | Morning | Route 2 | 15.45 | Encouraged |
| Condition 24 | Participant 2 | Morning | Route 3 | 17.94 | Encouraged |
| Condition 25 | Participant 2 | Night | Route 1 | 10.52 | Avoid |
| Condition 26 | Participant 2 | Night | Route 2 | 10.42 | Avoid |
| Condition 27 | Participant 2 | Night | Route 3 | 18.38 | Avoid |

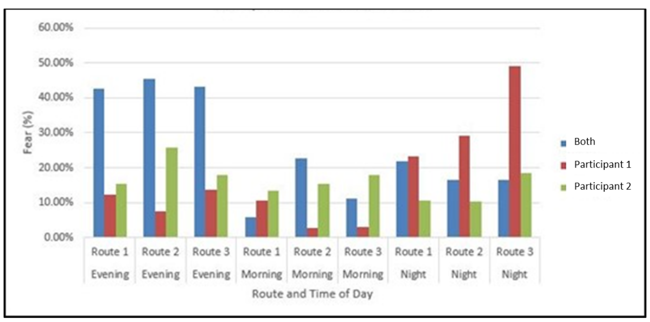


**Figure 3: Fear detection in all experimental conditions for all the participants.**

evening trials when both participants were involved, where fear levels were considerably high. This may be attributed to several limitations encountered during the series of trials involving both participants, which can be considered as anomalies since the other trials involving both participants showed lower fear levels during the morning settings and higher levels during the night conditions.

The results presented in Table 2 depict the identified fear levels along the route and the corresponding decision made by the proposed model whether to encourage or avoid the route, based on the given conditions. The analysis reveals that the model's decision-making process was based on the level of detected fear, where routes with higher detected fear were labeled as 'Avoid', while routes with lower fear were classified as 'Encouraged'. This demonstrates the application of decision-making in a realistic scenario, as intended in the introduction.

Furthermore, the results show a significant difference in the overall fear levels detected across trials. In some trials, the rate of detected fear was almost 50%, which was noticeably higher than the trials where the fear detection was less than 10% across the routes.

## 5 CONCLUSION AND FUTURE WORK

This paper proposed a model that takes into account fear detection in human decision making. Using video streams of human facial expressions combined with navigational information of different routes, a model was developed which used the amount of fear detected in participants faces to advice on how safe different routes were under different conditions. Quantitative analysis of the results obtained showed overall fear detected within the Video Footage varied from scores close to 0% of overall fear detected, and scores of almost 50% fear detected within the frames of the video showing that there was indeed a large variation of fear across each of the individual trials. Additionally, the trial predicted to have the highest level of fear, had the highest level of fear identified within the lone Experimenter at Night where the visibility levels are lowest along the route that was more out the way of busy streets in comparison of which had been decided as the route to most avoid by the application.

Further improvements would be required to the proposed system and would benefit applications such as Google Maps, where by more data would be collected such as within the experiments to record people across a given route. By classifying environments such as: shopping strips, alleyways, or even residential areas. A classification of the level of fear per environment rather than per route as within the experiments would help generate a more generalisable set of routes that can be applied within a Maps application. If collected on a large scale and significance is shown, there could see a similar set of results produced as within the program so routes showing higher levels of fear would tend to be recommend to users to avoid the given route taking into account the conditions.

Another application could see areas, particularly within the healthcare sector of which could largely be applied to patients, where the fear levels of patients can be assessed. Should the patients show high levels of fear the application could decide whether the patients may require social support; Additionally, this could be used within the classification of phobias for patients where the subject involved would be presented with a fear-invoking object or image for example, and using live streaming of the footage could determine that the subject may have a slight phobia or a high amount of phobia based on the amount of fear classified.

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