Exploring Machine Learning Applications for Biophilic Art Displays to Promote Health and Well-being

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ABSTRACT

Research has shown that the use of biophilic elements in public or private spaces is effective in alleviating stress, improving mental well-being, and increasing innovativeness in the general public. Studies reveal that exposure to Biophilic art can improve an individual's mental well-being. Many urban settings have few natural representations hence, the goal of our research is to use machine learning algorithms to develop a novel digital biophilic art categorization and display system to promote mental health and well-being. An initial survey conducted indicates a strong correlation between biophilia and positive emotions. We applied classification algorithms to develop an artwork recommendation system based on self-reported emotional responses to biophilic art pieces. Initial findings suggest a reduction in negative emotions and an increase in positive emotions, whilst using the system. This supports machine learning for the categorization and recommendation of biophilic art. It is in line with the importance of the integration of nature into built environments, and advocates the expansion of biophilic art databases, using more inclusive, emotionally responsive art recommendation systems.

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CCS CONCEPTS

• **Computing methodologies → Machine learning algorithms**.

KEYWORDS

Biophilia, Art, Intelligent Building, Mental health, Machine Learning, Recommender system.

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1 INTRODUCTION

A sense of connection to nature benefits well-being [1, 5, 19, 27]. *'Biophilia'*, a love of life or living things, promotes the idea that humans thrive both mentally and physically when connected to nature. Rapid urbanization has led to a loss of natural elements in many living spaces, creating a disconnect from nature which contributes to discontent [10, 25, 26]. For instance, 25 percent of office workers complain that offices are not conducive to well-being [3]. Almost 64% complained that offices lacked natural elements and more than 60% insisted that there was a lack of artistic aesthetics [3]. The Human Spaces Survey [4] found that 58% of 7,600 offices in 16 countries lack flora. Given that exposure to natural environments enhances positive affect and reduces negative emotions (e.g. stress)[10, 23, 24], biophilic design should be widely promoted. Research has shown that exposure to biophilic artwork may have a similar effect [12, 27]. The current study, therefore, endeavours to promote biophilia by curating digital biophilic artworks, using machine learning algorithms. Such a collection could be displayed using digital units to promote well-being in private and public settings. We hereby discuss our motivation, the methods for building the artwork classifier and recommendation system, the results of our techniques, and finally the key conclusions and future scope.

2 BACKGROUND STUDY AND MOTIVATION

The biophilic framework proposes that people have an innate attachment to the natural environment and thrive mentally and physically in natural settings. This concept, *biophilia*, was first coined by Erich Fromm in 1973 [6] and was further popularised by Edward O. Wilson in 1984 [22], who proposed the *Biophilia Hypothesis*. Relationships between humans, nature, and built environments, as studied from the perspective of architectural design [2], show that people thrive better when biophilic features are included in the built environment. While biophilic design focuses on including nature in urban settings, biophilic art attempts to strengthen our connection with the natural world through artistic expression. Whilst the representation of nature in art is not new, the concept of biophilic art is relatively recent. Art interventions have a positive impact on health across several conditions (e.g., dementia, depression, and Parkinson's disease [14]). For example, engagement with arts and culture results in a higher level of subjective well-being. However, there is limited research on the impact of biophilic art specifically.

The classification of paintings is a complex and multifaceted task, specific systems used often depend on the context and requirements. Common systems used to organize art include theme, subject, iconography, medium, artistic movement, time, patronage, and biography of key individuals (i.e., artists, collectors, geography). However, there is no existing categorization based on biophilic attributes, or indeed, any other health or salutogenic quality. Furthermore, there is a lack of validated scales to measure the emotional responses of the biophilic arts. A key advantage of digital technology is that it can automate many tasks, required for arts classification and recommendation, at a low cost. A key method used in the current study is Computer Vision [18], which is a field of artificial intelligence that focuses on enabling machines to interpret and process visual data from the world. It combines techniques from image processing, pattern recognition, and machine learning to enable applications like image and video recognition, object detection, and scene reconstruction. Painting categorization methods have been developed using automated categorization processes based on the signature styles of the painters and schools of the paintings, with accuracy rates between 70% to 80% [8, 9, 11, 13]. The current interdisciplinary approach uses artificial intelligence technologies to automate the curation and display of art, based on biophilic attributes and emotional responses, to promote health and well-being. That is, we have implemented state-of-the-art computer vision algorithms to identify biophilic attributes and emotional responses of visual arts.

3 METHODS

The research tasks follow three stages: Data Collection, Data processing, and applications of ML algorithms.

3.1 Biophilic & Emotional Attributes

To the author's knowledge, no standard labels for Biophilic design in art are defined. We have defined the "*Biophilic Attributes of Art*" based on the most established Biophilic characteristics for architectural designs defined in *Nature Inside: A Biophilic design guide* [2], *p5*;

- *Nature in the Paintings* with subcategories: Connection with Nature, Natural Organisation, Presence of Water, Presence of Animals, Presence of Plants or Fungi, Varying Light.
- *Natural Analogues in Paintings* with subcategories: Biomorphic shapes, Natural materials, and Complexity in order.
- *The Nature of the Paintings* with subcategories: Unimpeded views, Refuge, Mystery, Risk, and Awe

We have used the existing validated Positive Affect Negative Affect Scale (PANAS) Items [21] for defining the "emotional attributes of Biophilic arts" (EABA). **Positive Emotions**: *'Relaxed, Calm', 'Proud, Grand', 'Inspired, Amazed', 'Happy, Cheerful', 'Determined, Confident', 'Safe, Cosy', 'Energized, Excited', 'Nourished, Fulfilled', and 'Attentive, Concentrating'*. **Negative Emotions**: *'Upset, Distressed', 'Shy, Bashful', 'Sad, Downhearted', 'Hostile, Angry', 'Ashamed, Guilty', and 'Afraid, Frightened'*

3.2 Data and Resources

Since no previous research exists that uses machine learning to classify artworks based on biophilic traits, there is no publicly available dataset for the task. To start the data generation process, we performed a survey consisting of selected images. The selection of these images was achieved with the help of professionals in the fields of art, psychology, computer science, and biophilic building designs. We curated the dataset from scratch using artworks from the public domain and conducted several surveys. For this study, we have used 872 images of artworks primarily paintings and some photographs of sculptures from the Art Institute of Chicago's public gallery, all of which are in the public domain.

We created 50 separate surveys where participants were presented with 20 images of artworks and were requested to indicate the dominant biophilic characteristic and their emotional response, based on the attributes defined in Section 3.1. We streamline the number of biophilic attributes and categorize a subset of randomly selected 20 artworks from a data store of 872 artworks for each survey. Therefore, for each question, a different artwork would be seen by the participant, but the options would be the same within all the surveys. In total 200 participants participated in taking the surveys, their choices against each image were recorded, and the correlation between biophilic attributes and emotional responses was studied. With the help of this correlation, we built a simple recommender system that is capable of recommending biophilic artworks to users based on several criteria like emotional state and the time of day.

3.3 Machine Learning Techniques for Biophilic Classification and Predicting Emotional Response from Images

To train a machine learning classifier we require a diverse dataset, to expand the dataset, we formulated a technique where a pre-trained

ResNet50 [7] model was used to extract features from images that have received the highest response from the survey conducted for each of the 14 biophilic categories, defined in Section 3.1. 'Features' in an image refer to the identifying attributes or characteristics, e.g., patterns, edges or corners, texture, etc. ResNet50 model uses several techniques commonly used in most deep-learning models like the convolutional layers comprising filters to detect patterns, textures, shapes, etc., the pooling layers for dimensional reduction whilst retaining all meaningful information, and the residual blocks to handle the efficiency of the model. To extract features from images we simply remove the last layer of the model, i.e. the Fully Connected Layer, and the output 'Features' is a feature vector representing all interesting characteristics of the image. A pre-trained ResNet50 model has been trained on large-scale datasets like ImageNet, which makes the model deft at extracting generic features from images which is very important at this stage of our experiment. We used several new artworks from the public gallery of the Art Institute of Chicago to perform the next step of annotation. The same ResNet model was used to extract features from the new images, and a cosine similarity algorithm was used to compute the similarity of these new images with the images representing the 14 biophilic categories. Cosine similarity is defined by the below formula:

$$\mathrm{sim}(v_i, w_j) = \frac{v_i \cdot w_j}{\|v_i\|\|w_j\|} \tag{1}$$

where v_i and w_j are the two input vectors. $\mathrm{sim}(v_i, w_j)$ denotes dot product, and where $\|v_i\|$ and $\|w_j\|$ are the Euclidean lengths. The new images were given the label of the biophilic category of the most similar image. This way we created a diverse dataset of 10,000 images and their annotations representing the dominant biophilic characteristic.

This dataset was used to train a classification model capable of predicting the biophilic traits. For our task, the dataset has been divided into training and validation sets in a ratio of (7:3) to train the model and then validate the performance. We implemented several data augmentation tasks like normalization, random clipping, adding noise, flipping, and shearing, these are standard tools to make the dataset more diverse and robust. For the next stage, we developed a machine learning model that would effectively classify images based on their dominant biophilic traits, for this purpose, we used several popular classification models like a pre-trained ResNet50 [7], Swin Transformers [15], and DEIT [20]. A ResNet-50 is a popular deep neural network, it has a depth of 50 layers and uses a residual block to build the architecture. A residual block consists of several convolutional layers where the input of a block is combined with the output using skip connections. This skip connection makes it easier for the network to train by learning the difference or residual between the output and the input, they also help in improving the efficiency of the model by overcoming model overfitting. In comparison with other deep-learning models, ReNet50 is relatively computationally efficient without compromising accuracy. A DEIT is inspired by transformer-based architectures initially designed to perform Natural Language Processing (NLP). A DEIT has been specifically designed to achieve high performance using smaller datasets, hence most apt for our task. The DEIT model uses transfer learning through a technique called *distillation through attention* and tokenises the images by creating a sequence of patches that do not overlap for processing by the transformer. A Swin Transformer on the other hand uses shifted windows to capture multi-scale information, unlike the DEIT, Swin transformers process images hierarchically, averaging features across stages to understand context locally and globally. DEIT and Swin are state-of-the-art transformer-based models used for image classification tasks

Our next task is to build a machine-learning model that would predict the percentage of each of the 15 Emotional responses (ER) (discussed in Section 3.1) present in each image. We created a new dataset using only the 872 images used for the survey where annotations of each image were given by the percentage vote of each of the 15 ERs. We developed a CNN-based regression model comprising an encoder and a decoder, an Encoder extracts features from an image and a decoder uses the image features to predict the probabilities of each label. We used OpenAI's CLIP [16] model as an encoder to generate image embeddings and then used the image embeddings to train a decoder model that would give us the probability per label. The CLIP model [16] is a state-of-the-art model, that is trained on 400 million image-text pairs, which makes it extremely robust in generating image embeddings. Image representations or embeddings are representations of an image in a lower vector space, embedding models are designed to transform complex visual data into a concise representation in a lower dimensional vector space while retaining the unique patterns and features of the image. These image embeddings can be used in encoder-decoder models like ours to perform various tasks. CLIP [16] uses a Vision Transformer (ViT)-B/32 [17] to generate embeddings of an image. Our decoder model is very straightforward, comprising 3 fully connected networks and batch normalization and ReLu layers in between. The final output is a unidimensional vector representing the probabilities of each emotion label, Figure 1 summarizes our decoder model.

3.4 Recommender System

This project aims to recommend biophilic artworks to people based on their emotional state. For example, if a person is feeling *'Sad, Downhearted'* and requests 'cheering up', our recommender would recommend images labelled as *'Happy, Cheerful'*, similarly our system would recommend images with the label *'Relaxed, Calm'* to someone who wishes to relax. To build a simple recommender system we need to establish the correlation between the biophilic and the emotional labels. The current method identified images for which participant reports suggested consensus in biophilic labels, and presented the percentage that each emotion was expressed. Finally, aggregate the percentage of emotions for each biophilic class creating a correlation matrix.

Next, we designed a second survey, where participants indicated their affect state by rating each of the 15 emotions between 1 (least intense) to 5 (most intense). Using the correlation matrix, the algorithm finds the appropriate biophilic traits, and the algorithm then displays 20 images from these biophilic classes. For example, if the dominant emotion is 'Sad' since it is a negative emotion, the algorithm chooses the biophilic trait that has the least percentage of participants choosing the emotion 'Sad'. If the dominant emotion is 'Relaxed', since it is a positive emotion, the algorithm recommends images for biophilic traits with a higher percentage of other

```
Decoder(
    (fc1): Linear(int_features=512, out_features=256, bias=True)
    (batch_norm1): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu1): ReLu()
    (dropout1): Dropout(p=0.2, inplace=False)
    (fc2): Linear(int_features=256, out_features=128, bias=True)
    (batch_norm2): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu2): ReLu()
    (dropout2): Dropout(p=0.2, inplace=False)
    (fc3): Linear(int_features=128, out_features=5, bias=True)
)
```

Figure 1: Summary of the Decoder model

positive emotions. Additionally, the recommender system identifies the least positive emotion and tries to boost it by showing images from the biophilic class that promote that emotion. This survey was designed to capture the user's perception of the recommendation system.

4 RESULTS AND ANALYSIS

4.1 ML Classification Results

Table 1 tabulates the comparison of the accuracies of the models used on the validation dataset. As seen in the table the accuracies are very mediocre and the machine learning models suffer from overfitting. We identified the following shortcomings of the model, firstly the initial dataset used consists of only 872 images for all the 14 biophilic categories, which is exceedingly small for machine-learning models to train on. Moreover, we used cosine similarity to expand our dataset, this metric enables consideration of images that visually resonate most with participant responses in mind. Using cosine similarity to assign labels to images is not an ideal method as it has a lot of shortcomings. It fails to capture the spatial features because it concentrates only on the angle between the vector representation of the images. This method is also insensitive to any noise and is unable to extract complex features from the images. Thus, this method mislabels a lot of artworks to incorrect biophilic categories. In the future, we plan to get labels from more surveys or manual annotations by experts. Furthermore, the dataset is unbalanced, with some biophilic traits being hugely underrepresented, thus the machine fails to learn the characteristics of these traits. The most crucial factor is we depended on the survey data to create our dataset, the survey contains a huge variability in responses, which in turn makes the dataset extremely biased and the AI model is not able to learn patterns to generalize. Also, certain biophilic tags like '*Risk*', '*Awe*', and '*Mystery*' are subjective and can be interpreted in many ways by the participants, this adds a lot of ambiguity to the data that cannot be explained by our model. To overcome the difficulties, for our ongoing work we have decided to remove any biophilic trait that has any emotional aspect in it like '*Risk*', '*Awe*', and '*Mystery*', and include only discrete biophilic labels which is a diversion from the traditional biophilic characteristics. We are also working on a muti-label classification algorithm that predicts all biophilic labels present in an image rather than just one dominant or prominent label.

For predicting the emotions from the artworks we used a regression model and to evaluate it we used the R-squared metric. R-squared is a statistical metric used in regression models to quantify the extent to which the independent variable can explain the variation in the dependent variable. The formula is given by:

$$L = \frac{\sum_i^N (y_i - p_i)^2}{\sum_i^N (y_i - \mu)^2} \tag{2}$$

Where y_i is the actual value, p_i is the predicted value, μ is the mean of the actual values, and N is the sample size. We achieved an R-squared score of 0.82 on the training dataset and an R-squared score of 0.063 on the validation dataset. This indicates the model is suffering from overfitting. Training a machine-learning model to predict emotions from artworks is very tough, to achieve this task we need more annotated data.

4.2 Recommendation feedbacks

For our next task, we built a recommender system that would take a user's emotional state as input and recommend Biophilic images. To achieve this, we used only the images from the first survey where participants had a consensus on the most dominant biophilic trait. Then we computed the percentage of each emotion per Biophilic class. Figure 2, illustrates the most dominant emotions per Biophilic class. As can be seen, except for the *'Risk'* category where a majority of the participants expressed *'Afraid, Frightened'*, for all the other classes participants felt positive with most feeling *'Relaxed, Calm'* or *'Attentive, Concentrating'*.

We then created a table for each biophilic trait, and the fraction of emotional labels as indicated by participants of the first survey. Table 2 shows the fraction of each emotion for a Biophilic category. This correlation table was used to build our recommender system. To test the performance of our recommender system we designed a second survey where participants are requested to indicate their emotional status by rating the 15 emotions on a scale of 1 to 5, with 1 being the least and 5 being the highest. Then these ratings are used by the recommender system to recommend 20 Biophilic artworks, each appearing one after the other with a viewing time of 5 seconds. Once all the 20 images have been displayed participants are once again requested to indicate their emotional state. We have taken 50 surveys and compared the before and after emotional responses of the users.

Table 1: Performance Metrics of the Different Classification Algorithms

Models	Accuracy of Training DS (%)	Accuracy of Validation DS (%)
ResNet50	67	69.30
DEIT	66.70	68.40
Swin Transformers	67.60	68.80

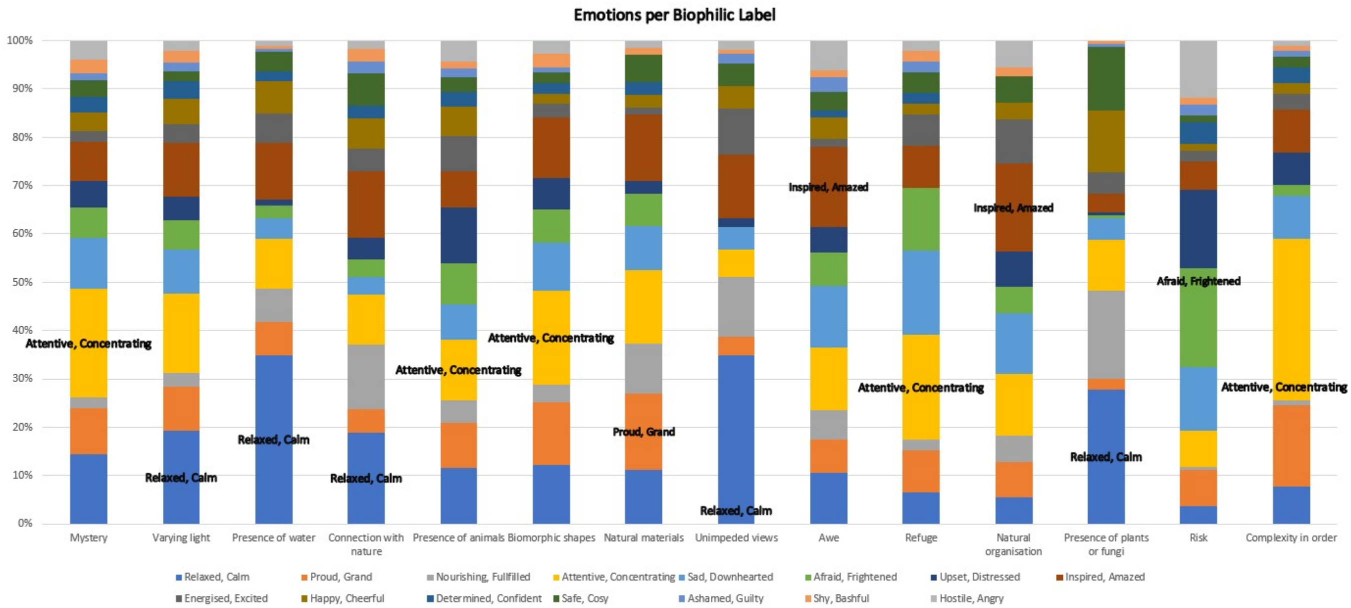

Figure 2: Association between emotional response and biophilic attributes

Table 2: Fraction of emotions per Biophilic Category as per the survey

Biophilic Label	Emotional Label														
	Relaxed, Calm	*Proud, Grand*	*Nourishing, Fullfilled*	*Attentive, Concentrating*	*Sad, Downhearted*	*Afraid, Frightened*	*Upset, Distressed*	*Inspired, Amazed*	*Energised, Excited*	*Happy, Cheerful*	*Determined, Confident*	*Safe, Cosy*	*Ashamed, Guilty*	*Shy, Bashful*	*Hostile, Angry*
Mystery	0.144	0.095	0.023	0.225	0.107	0.062	0.055	0.081	0.022	0.039	0.033	0.034	0.014	0.028	0.04
Varying light	0.192	0.092	0.029	0.163	0.092	0.061	0.047	0.113	0.037	0.053	0.037	0.021	0.018	0.024	0.021
Presence of water	0.349	0.069	0.069	0.102	0.043	0.026	0.013	0.117	0.061	0.066	0.02	0.041	0.005	0.008	0.01
Connection with nature	0.189	0.047	0.134	0.103	0.037	0.037	0.045	0.137	0.047	0.063	0.026	0.066	0.024	0.026	0.018
Presence of animals	0.116	0.092	0.048	0.126	0.072	0.085	0.116	0.075	0.072	0.061	0.031	0.031	0.017	0.014	0.044
Biomorphic shapes	0.121	0.13	0.037	0.195	0.098	0.07	0.065	0.126	0.028	0.019	0.023	0.023	0.009	0.028	0.028
Natural materials	0.112	0.158	0.102	0.153	0.092	0.066	0.026	0.138	0.015	0.026	0.026	0.056	0	0.015	0.015
Unimpeded views	0.349	0.038	0.123	0.057	0.047	0	0.019	0.132	0.094	0.047	0	0.047	0.019	0.009	0.019
Awe	0.106	0.068	0.061	0.129	0.129	0.068	0.053	0.167	0.015	0.045	0.015	0.038	0.03	0.015	0.061
Refuge	0.065	0.087	0.022	0.217	0.174	0.13	0	0.087	0.065	0.022	0.022	0.043	0.022	0.022	0.022
Natural organisation	0.055	0.073	0.055	0.127	0.127	0.055	0.073	0.182	0.091	0.036	0	0.055	0	0.018	0.055
Presence of plants or fungi	0.278	0.022	0.183	0.106	0.044	0.006	0.006	0.039	0.044	0.128	0	0.133	0.006	0.006	0
Risk	0.037	0.074	0.007	0.074	0.132	0.206	0.162	0.059	0.022	0.015	0.044	0.015	0.022	0.015	0.118
Complexity in order	0.078	0.167	0.011	0.333	0.089	0.022	0.067	0.089	0.033	0.022	0.033	0.022	0.011	0.011	0.011

From the 50 surveys conducted, we computed the mean response for all 15 emotions before and after exposure to the Biophilic artworks, Figure 3 a & b shows the average before and after emotional ratings of all 50 participants. We could see some trends emerging, and our prototype was successful in boosting some of the positive emotions like *'Relaxed, Calm', 'Inspired, Amazed', 'Energised, Excited', and, 'Happy, Cheerful'*. Additionally, negative emotions

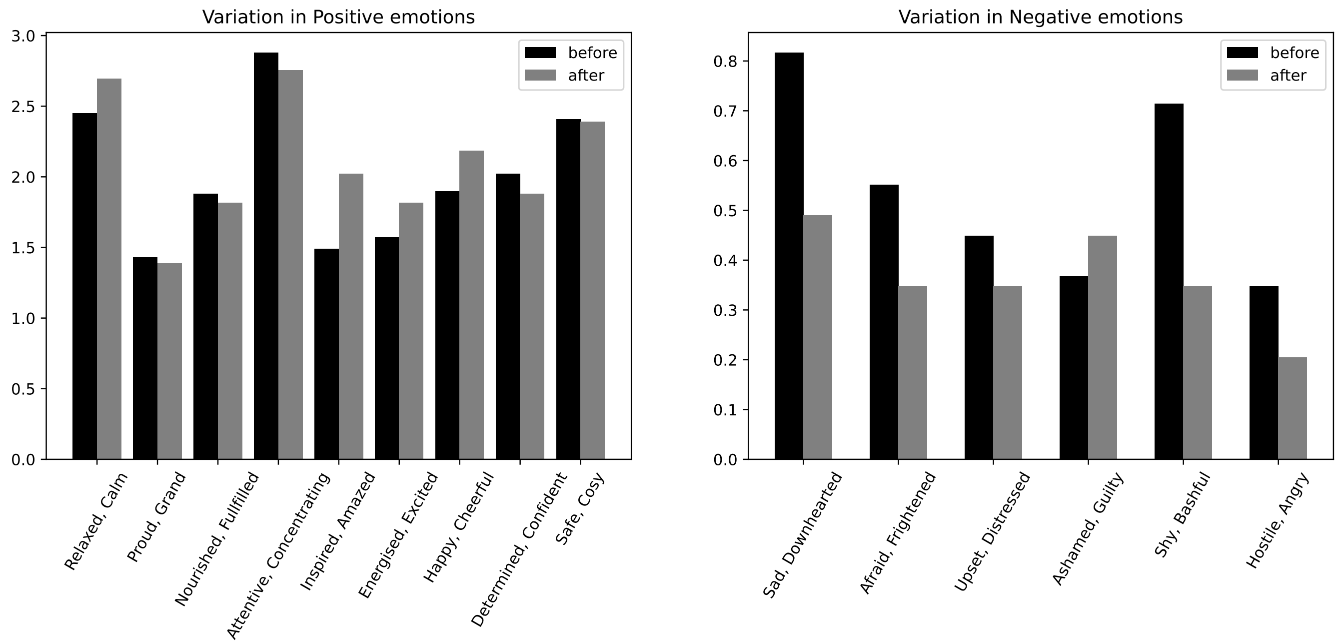

Figure 3: Variations in emotions for Proposed Recommender System

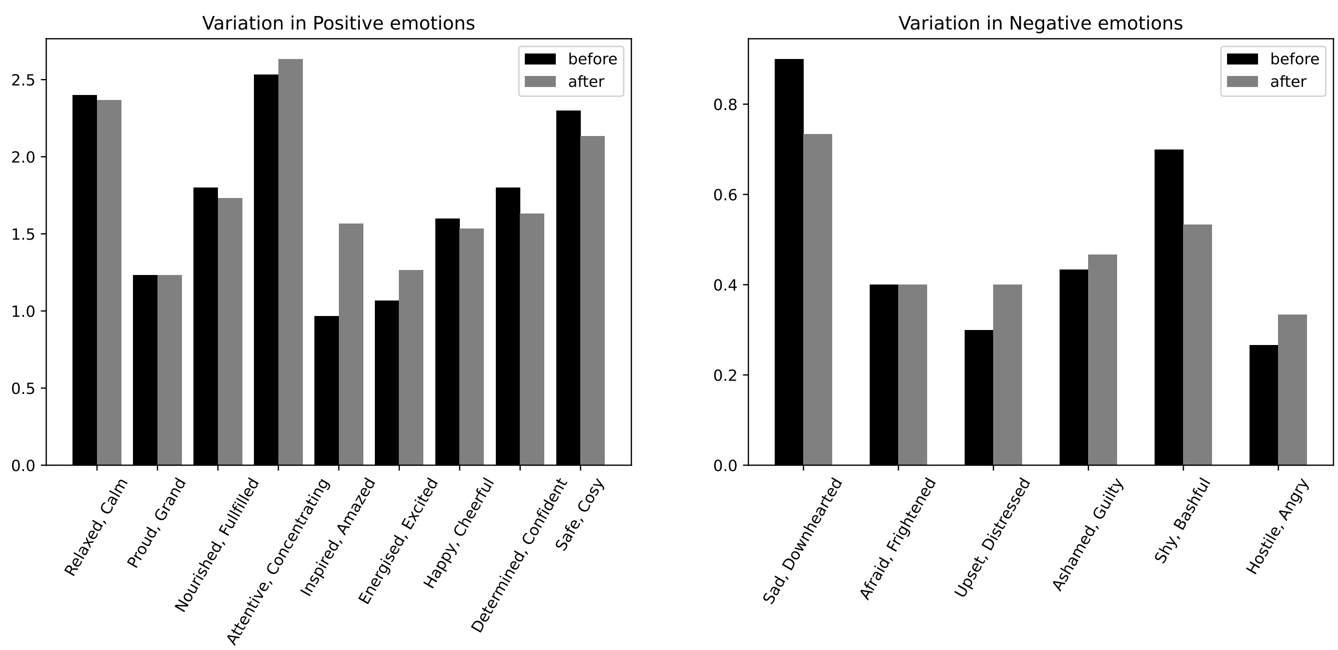

Figure 4: Variations in emotions for Random Recommendations

like '*Sad, Downhearted', 'Afraid, Frightened', 'Upset, Distressed', 'Shy, Bashful', and 'Hostile, Angry'* were visibly reduced.

The results of the second survey indicate that exposure to Biophilic artworks and images can boost positive emotions and reduce negative emotions as shown in Figure 3. The responses are the average emotional response from before and after exposure to Biophilic artwork. To determine the performance of the recommender system we have compared the results with random recommendations, where the system recommended artworks that were more neutral and non-significantly Biophilic. Again we have used average responses from before and after viewing the artwork. As seen in Figure 4 there is no underlying emotional pattern for randomly recommended artworks.

5 CONCLUSION AND FUTURE WORK

Engagement with nature and arts improves the cognitive abilities of children and young people. In the interconnected worlds of the Digital Age, arts can help the urban population to engage with nature more effectively and meaningfully. A key aim of this project is to integrate Artificial Intelligence and Machine Learning algorithms to produce an intelligent and personalized recommendation system to improve users' mental health. This research project is to fill in the existing gap for developing AI-based digital biophilic therapeutic systems. Initial results show challenges in categorization due to the complexities of biophilic and emotional traits in art but indicate the potential of the recommender system in aligning artworks with user emotions.

Key biophilic design patterns have been developed by Browning [2], but they can't be directly translated to categorize and analyze biophilic artworks. A set of net biophilic emotional metrics was developed and a public survey was carried out and results show a positive correlation between positive emotional responses and biophilic attributes. The top four most significant emotional responses are relaxation, attentiveness, pride, and inspiration with a strong correlation with the presence of plants, natural organization, and natural materials Respectively, negative emotions like *'Afraid, Frightened'*, *'Upset, Distressed'*, and *'Sad, Downhearted'* have a strong correlation with *'Risk'*.

The initial phase of our study is devoted to building a biophilic classification algorithm that categorizes artworks into the corresponding biophilic characteristics with the help of state-of-the-art deep-learning techniques. The experiment performed using ResNet and transformer models provided suboptimal results. To train a machine learning model successfully, we need a bigger and better-annotated dataset curated from multiple sources, with paintings from various movements, styles, and genres to increase the generalizability of the model. A better database with more evenly distributed tags can also be developed to improve classification accuracy, additionally, including AI-generated or synthetic data, will not only reduce problems related to underrepresentation but also make the dataset more diverse. For classifying emotions from artwork, we plan to conduct more surveys to gather emotional responses to artworks. Furthermore, explore multi-modal models that utilise images and texts in sophisticated techniques like early/late fusion and ensemble to predict emotions. This artificially intelligent model can help artists in sorting their artwork by the various biophilic characteristics, and create a curated collection of nature-inspired art. We also plan to revisit the Biophilic categories, the categories that have emotional aspects like *'Mystery'*, *'Risk'*, and *'Awe'* which adds a lot of ambiguity to our study. In subsequent studies, we plan to include only the objective biophilic categories and move the emotional aspects to the Emotional labels.

The focus of this project is to improve the health and well-being of the occupants of the built environment. The project is targeted to the public to improve the mental health and well-being of people within the environment of the display device. Our simple recommender system was able to boost some positive emotions like *'Relaxed, Calm'*, *'Inspired, Amazed'*, *'Energised, Excited'*, and, *'Happy, Cheerful'* and reduce most of the negative emotions. All the images used for the survey have some therapeutic value hence more research is required to understand the emotional effects of longer periods of exposure to them. Biophilic artwork recommendations can be developed based on a myriad of factors like the weather conditions, primarily temperature, time of day, e.g., morning, noon, or evening, personal preferences, circadian rhythms, and emotional status of the user. We are also interested in using AI-based classification models to predict emotions from artworks and building a personalized recommender system that recommends artworks based on Biophilic traits, emotional state, personal circadian cycles, environmental conditions, etc. In this survey, the participants were exposed to Biophilic artworks for a very short period of just 20 seconds, and more research is required to study the effects of longer periods of prolonged exposure.

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