SmartInternz Guided Project

AI Art Detection
Project Report

1. Introduction

1.1 Project Overview

AI art is an exciting and quickly developing topic that has emerged in recent years from the fusion of artificial intelligence (AI) with the art world. This field includes the creation, manipulation, and replication of artistic content using cutting-edge machine-learning methods. It is essential to develop techniques for reliably detecting and differentiating between AI-generated artworks and those produced by human artists as AI-generated art becomes more prominent in galleries, internet platforms, and cultural conversations. This study explores the difficulties, approaches, and effects of detecting artworks created by artificial intelligence. It focuses on the crucial topic of AI art detection.

For the art world and society in general, the development of AI-generated art brings both potential and challenges. On the one hand, AI provides creative and experimental tools for artists, allowing them to foray into new expressional spheres. On the other hand, the quick development of AI techniques has resulted in the creation of works that question conventional ideas of originality, authorship, and the function of human creativity. There are concerns about the moral ramifications of giving artificial intelligence-generated art a monetary value as it enters galleries and the art market.

There are different types of art, each with its own distinct styles and techniques. Robust training data and sophisticated feature extraction approaches are needed to build models that can correctly categorize and distinguish between these various types. Large and superior-quality datasets are essential for developing precise AI algorithms for art detection. However, because of factors like variances in lighting, image quality, and artistic interpretation, many artworks may have minimal data accessible or the data may be noisy and inconsistent.

1.2 Purpose

This study's main objective is to address the demand for trustworthy and effective AI art-detecting techniques. Examining the numerous methods and approaches designed to discern between art produced by AI and art produced by humans. Analyzing brushstrokes, texture, color schemes, and other visual elements may be necessary for this, along with taking metadata and the context of the image into account. The ability of AI models to accurately mimic a variety of artistic styles makes it hard to distinguish between AI-generated art and human-made art. Taking into account a variety of visual and contextual indicators that could offer insights into an artwork's origin, this paper aims to investigate the technological developments and tactics used to recognize AI-generated art.

2. LITERATURE SURVEY

2.1 Existing Problem

Angus Forbes [1] explores the development of Artificial Intelligence and Machine Learning in most recent years and proposes implementations of these aforementioned concepts to produce Creative AI. The research emphasizes the use of algorithms that identify, manipulate, or replicate data in order to facilitate generative AIs or multi-modal mapping of the user input to media output to learn feature detection at a deeper level.

Eva Cetinic's and James She's [2] research gives a comprehensive examination of the two aspects of artificial intelligence that can be used in art: one being for the specific of analysis of art and how it can be applied to collections of digital artworks; and the other being how AI can be utilized for creative purposes and production of new artwork. In the context of AI training, various practical and theoretical aspects of AI art are taken into consideration for a concise projection of AI art's future progression with respect to detection, classification, and multimodal mapping.

Michael Mateas [3] talks about expressive AI which as quoted by the authors is the "inter-discipline of AI-based cultural production, combining art practice and AI-research practice" exploring the possibilities of creative AI and applications of Creative AI also by giving some context to the influence of such AI on the life of people either positive or negative. The research also sheds light on human-AI interactions and finally tops it off with how Expressive AI that can include generational functions can be more than just an application or a tool in a far wider scope.

Mateja Culjak et [4] paper explains and details an approach to an automatic art genre classification and how to go about fine-tuning the model of such caliber to give efficient speeds and efficient feature extraction. Provides a large and articulate data set with over \textit{15,000 images} over six classes of various types of paintings on which using image detection extensions of CNN have had different success rates for each class providing us some idea on the working of CNN in learning features of art work.

Maciej Wiatrak et [5] provides an overview of the challenges faced in training Generative Adversarial Networks (GANs) and introduces the purpose of the survey, which is to comprehensively review the methods proposed in the literature for stabilizing GAN training. It mentions the instability problems encountered during GAN training, such as non-convergence, vanishing or exploding gradients, and mode collapse, and highlights the importance of addressing these issues for effective GAN training

Ahmed Elgamma et [6] introduces a new system called Creative Adversarial Networks (CAN) for generating art. The system learns about different artistic styles and enhances creativity by deviating from those styles. The authors conducted experiments showing that human subjects couldn't distinguish art generated by CAN from art created by contemporary artists displayed in top art fairs.

Vivek Kanji malam [7] is a Neural network research that aims to classify digits and doodles similar to the functioning of the mnist dataset. The model used in this research is trained using the Cifar10 dataset also in addition with the Minst dataset to identify over 10 classes of objects.

Goodfellow et al [8] introduces the concepts of a Generational Adversarial Network. The text discusses the phenomenon of adversarial examples, which are inputs that are intentionally perturbed to cause machine learning models, including neural networks, to misclassify them with high confidence. Early explanations focused on nonlinearity and overfitting, but the authors argue that the primary reason for neural networks' vulnerability to adversarial perturbations is their linear nature. They propose a fast method of generating adversarial examples and show that adversarial training can provide additional regularization benefits.

Alzantot et al [9] is a brief study on the use of Synthetic data and model architectures that are able to create synthetic data capable of providing more data for models to train more adequately similar to a kind of augmented data. Explains sophisticated models that use generators and discriminators and their purposes.

Castellano et al [10] This paper gives an overview of deep learning approaches used in the field of visual arts, specifically for pattern extraction and recognition in painting and drawing. Recent advancements in deep learning and computer vision, along with the availability of large digitized art collections, have provided opportunities for computer science researchers to develop automatic tools for analyzing and understanding visual arts. This deeper understanding can make visual arts more accessible to a wider audience, contributing to the dissemination of culture.

Goldberg [11] textbook on natural language processing explains in great detail the subsetted concept of deep learning. Provides the implementation of Deep learning models in the fields of NLP and LLM. The book provides a in-depth text on RNN and its variation such as LSTMs and their application and limitations.

Eva Cetinic's [12] studies the digitization of fine art collections that has led to an increase in the availability and preservation of artworks, making them accessible to a wider audience. This paper explores different methods of extracting image features to classify paintings by genre. By using a pre-trained deep convolutional neural network, the authors achieved an accuracy of 77.57\% in genre classification, highlighting the potential of computer vision techniques in automating the identification of painting characteristics and generating metadata.

Cetnic et al [13] studies the fine-tuning of Convolutional Neural networks of which are implemented in the context of fine art classification. With the increase of the digital art space, the research paper proposes a CNN network named CaffeNet, a modified CNN with five conv2d layers and three fully connected layers, using Relu activation functions. The research paper delves into a fine-tuning setup for the proposed CNN architecture and also analyzes the impact that domain-specific weight initialization [14] has on it.

Qian Xiang et [14] discusses fruit image classification as an important technology for profitable fruit-picking robots and increasing competitiveness in the global fruit market. Although deep learning, especially DCNN, excels at classifying images, the resource requirements make them unsuitable for resource-constrained contexts such as automated harvesting robots. To balance resource constraints and accuracy, the study uses MobileNetV2 lightweight neural network with transfer learning method. This approach replaces the upper layer of the pre-trained MobileNetV2 network with a convolution layer and a Softmax classifier, incorporating dropout to reduce overfitting. Through a two-step training process with the Adam optimizer, the proposed method achieves a classification accuracy of 85.12\% on a fruit dataset of 3,670 images. Compared to other networks such as MobileNetV1, InceptionV3 and DenseNet121, this hybrid network offers a favorable balance between accuracy and speed, making it possible for the network to be deployed on low power devices such as mobile phones

Dhananjay Theckedath and RR Sedamkar[15] discuss the importance of effect sensing in human-computer interface systems and present a study using convolutional neural network (CNN) with transfer learning method to detect 7 affect states. The article compares three pre-trained networks: VGG16, ResNet50 and SE-ResNet50, integrating the new architecture block. The networks were trained and evaluated on the image dataset, achieving validation accuracy of 96.8\%, 99.47\%, and 97.34\% for VGG16, ResNet50 and SE-ResNet50, respectively. The rating also takes into account accuracy and recall, indicating the ability to accurately detect effects across all networks, with ResNet50 being the most accurate.

Eva Cetnic et al [16] discusses the application of Convolutional Neural Networks (CNN) for fine art classification. The authors explore the use of CNNs for various art-related image classification tasks, including artist, genre, style, time period, and national artistic context classification. They also investigate the transferability of deep representations across different domains and demonstrate the practical applicability of their results in enhancing search systems for online art collections.

Gaozhong Tang et al [17] addresses the challenge of predicting crowd flows in urban areas by leveraging both spatial and temporal features. The authors propose a novel approach that extracts spatial features from city maps using convolutional neural networks and incorporates a sequence feature fusion mechanism to merge spatial and temporal features for accurate crowd flow prediction.

Jia Deng et al [18] discusses the introduction of a new database called "ImageNet," which is a large-scale ontology of images built upon the WordNet structure. ImageNet aims to provide a vast collection of annotated images organized according to the semantic hierarchy of WordNet, offering opportunities for research in computer vision and beyond. The paper highlights the scale, accuracy, diversity, and hierarchical structure of ImageNet and demonstrates its usefulness through applications in object recognition, image classification, and automatic object clustering.

Mondal et [19]Implies Artworks and paintings have been an important part of human civilization since ancient times, providing valuable insights into various subjects. Archiving digital versions of paintings helps preserve the works of different painters. In this study, a conventional Neural Network is used to classify artworks, focusing on both foreign and Indian painters, with an average accuracy of 85.05\%. Provides more proof that CNN's are able to feature extract learn art in a more atomic level.

Johnson et al [20] explores image processing tools that are capable of assisting historians and such. Research has been conducted in accordance with the Van Gogh and Kroller-Muller museums to create a data set consisting of 101 high-resolution gray-scaled images that can be used for image processing.

Mark Sandler et al [21] introduces a new mobile architecture called MobileNetV2, which improves the performance of mobile models across various tasks and model sizes. It also discusses the application of these models to object detection and semantic segmentation.

Kannan K[22] is a project on Kaggle that is a use case for the current problem that this paper tries to delve into and start. The project has achieved an accuracy score of 91.0\% with the assistance of the transfer learning mechanisms of MobileNetV2 architecture.

shen et al [23] This paper explores how with the advancement of artificial intelligence (AI) technology, art creation is becoming more diverse and interactive, driven by intelligent, data-driven content expression. AI aims to replicate human cognitive abilities, enabling natural responses, emotion decoding, and recognition of human traits. This has led to a shift in interactive art, focusing on integrated, interactive, and emotionally engaging artistic expressions that study natural human behavior and combine it with intelligent systems. In the context of the research article, the authors explore the intersection of AI technology and interactive art, analyzing their historical development and proposing the impact of AI on creative thinking, creative modes, and artistic experiences in interactive art.

2.2 References

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learning about styles and deviating from style norms. arXiv preprint arXiv:1706.07068, 2017.

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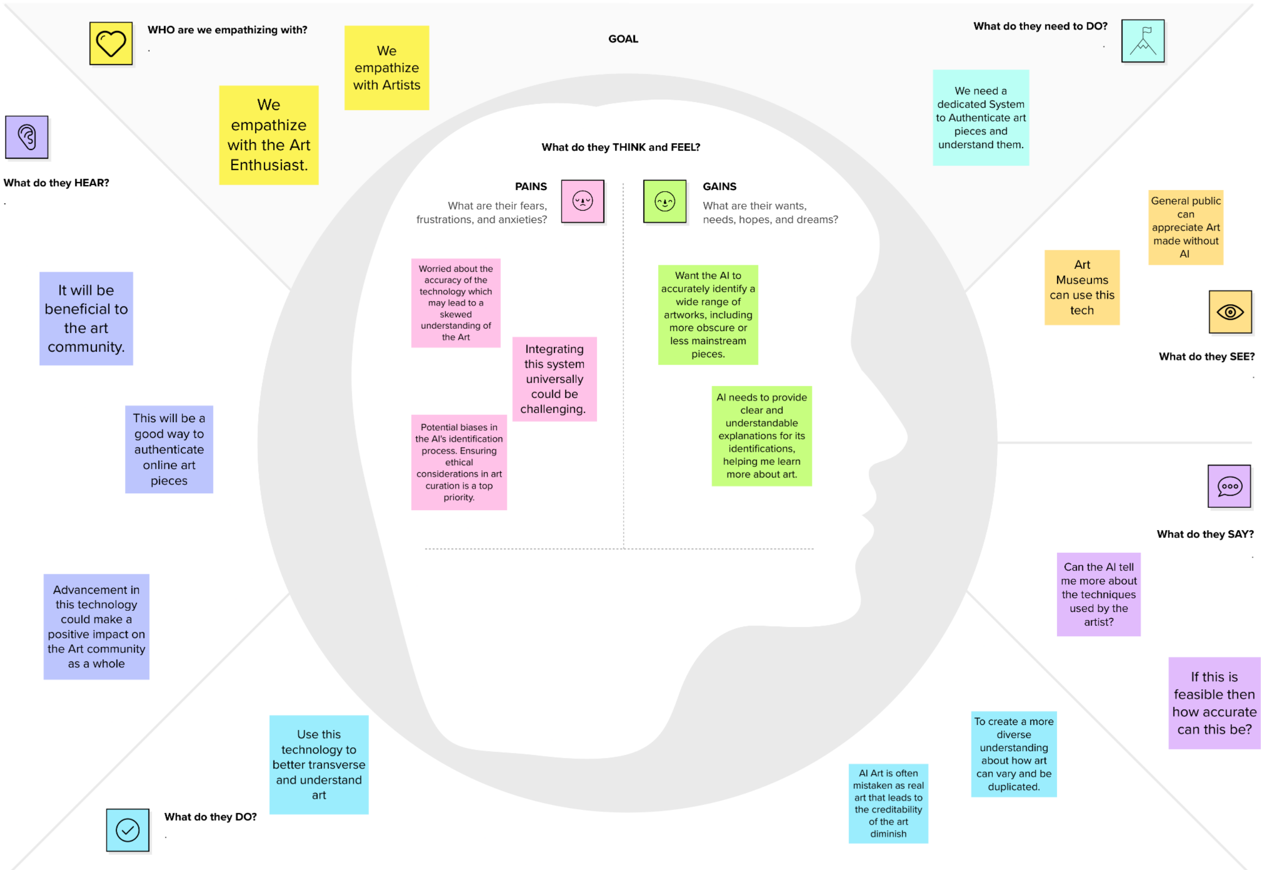
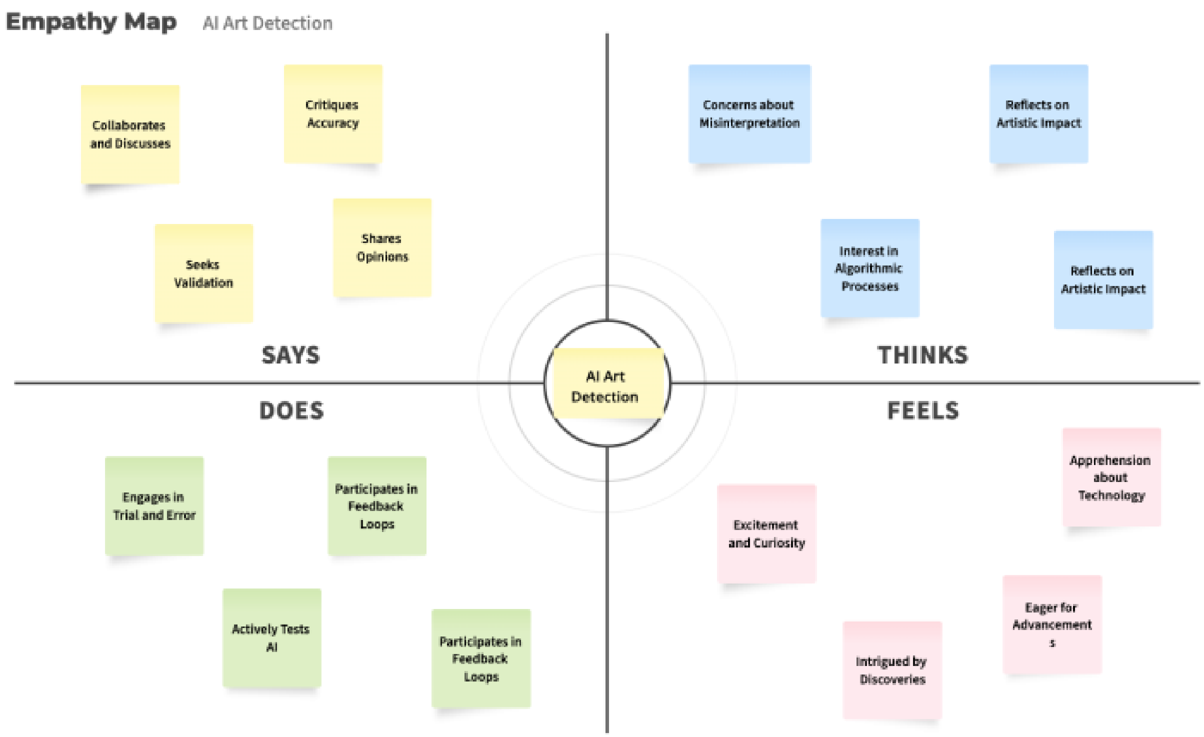
2.3 Problem Statement Definition

Differentiating between traditionally crafted and AI-generated images is becoming more and more difficult in the ever-changing landscape of digital art creation. The lack of a system specifically designed to categorize the place of origin of images makes it more difficult to verify their authenticity and creates concern in the art market. An AI Art Detection solution that focuses on determining whether or not an image is artificial intelligence (AI) generated is essential to address this. In the context of an increasingly AI-infused art landscape, such a system would be an essential tool for buyers, galleries, and collectors of art to ensure transparency, trust, and accurate attribution.

3. Ideation and Proposed Solution

3.1 Empathy Map


WHO are we empathizing with?
We empathize with the Art Enthusiast.
We empathize with Artists
GOAL
What do they need to DO?
We need a dedicated System to Authenticate art pieces and understand them.
What do they HEAR?
It will be beneficial to the art community.
This will be a good way to authenticate online art pieces
Advancement in this technology could make a positive impact on the Art community as a whole
What do they THINK and FEEL?
PAINS
What are their fears, frustrations, and anxieties?
Worried about the accuracy of the technology which may lead to a skewed understanding of the Art
Integrating this system universally could be challenging.
Potential biases in the AI's identification process. Ensuring ethical considerations in art curation is a top priority.
GAINS
What are their wants, needs, hopes, and dreams?
Want the AI to accurately identify a wide range of artworks, including more obscure or less mainstream pieces.
AI needs to provide clear and understandable explanations for its identifications, helping me learn more about art.
General public can appreciate Art made without AI
Art Museums can use this tech
What do they SEE?
What do they SAY?
Can the AI tell me more about the techniques used by the artist?
If this is feasible then how accurate can this be?
What do they DO?
Use this technology to better transverse and understand art
AI Art is often mistaken as real art that leads to the creditability of the art diminish
To create a more diverse understanding about how art can vary and be duplicated.



3.2 Ideation and Brainstorming

1

Brainstorming

The problem we aim to address is the detection of AI generated art from real art using AI and Machine Learning.

Smit

- Use labeled datasets to train supervised learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs).
- Use pre-trained models (like ImageNet) and refine them for AI Art Detection.
- Combining CNNs, RNNs, and SVMs, to improve overall accuracy.
- Use recurrent neural networks or other time-series models to analyze the evolution of art styles and use it for AI Art Detection.

Tharrun

- Utilize large image datasets to train convolutional neural networks (CNNs) and fine-tune them for tasks related to art detection.
- Use handcrafted features like color histograms, texture patterns, and shape descriptors to train Support Vector Machines (SVMs) to detect AI art.
- Utilize transfer learning with pre-trained Recurrent Neural Networks (RNNs) on sequential data.
- Develop an ensemble model combining the strengths of Support Vector Machines and Convolutional Neural Networks for detection

Rishabh

- Create a hierarchical CNN architecture in which the model first categorizes broad characteristics like art style, then in on specific details like objects or themes within artworks.
- Utilize pre-trained autoencoders to extract features from artworks, reducing dimensionality and capturing essential information for classification using machine learning models like SVM.
- Using ensemble learning method Random Forests to classify styles and genres.
- Develop a hybrid model that combines the interpretability of SVMs with the feature learning capabilities of CNNs for AI Art Detection.

Anmol

- Create a GANs to create synthetic artworks in particular styles, and use it to train a model to detect AI Art by differentiating between real and synthetic artworks.
- Using CNN to extract features from a labeled dataset and then using it for Detection.
- Using RNN on a sequential dataset to understand authentic art.
- Use Transfer Learning using pretrained CNN models on a image dataset to improve detection.

2

Grouping Ideas

Ideas Involving CNN

Use labeled datasets to train supervised learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

Utilize large image datasets to train convolutional neural networks (CNNs) and fine-tune them for tasks related to art detection.

Create a hierarchical CNN architecture in which the model first categorizes broad characteristics like art style, then in on specific details like objects or themes within artworks.

Using CNN to extract features from a labeled dataset and then using it for Detection.

Use Transfer Learning using pretrained CNN models on a image dataset to improve detection.

Ideas Involving Transfer learning

Use pre-trained models (like ImageNet) and refine them for AI Art Detection.

Utilize transfer learning with pre-trained Recurrent Neural Networks (RNNs) on sequential data.

Utilize pre-trained autoencoders to extract features from artworks, reducing dimensionality and capturing essential information for classification using machine learning models like SVM.

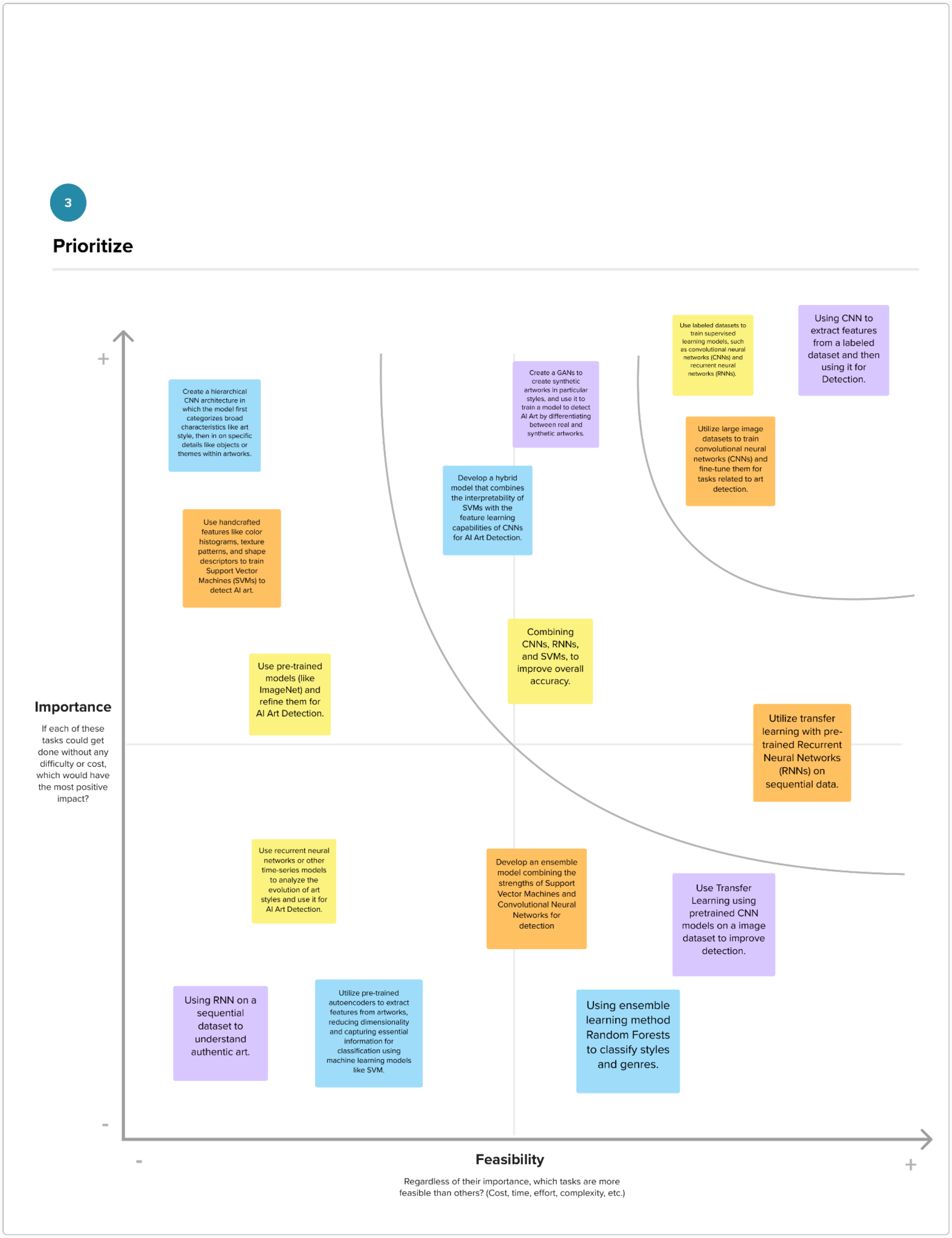
Use Transfer Learning using pretrained CNN models on a image dataset to improve detection.

Ideas Involving Ensemble methods

Combining CNNs, RNNs, and SVMs, to improve overall accuracy.

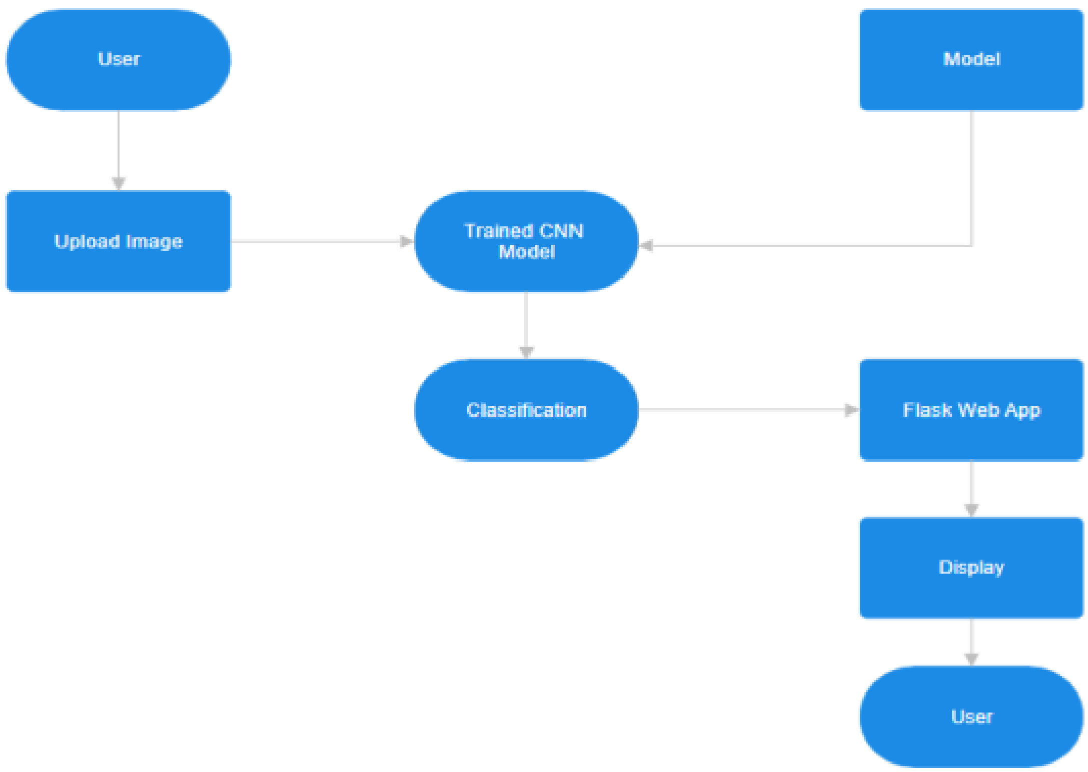
Develop an ensemble model combining the strengths of Support Vector Machines and Convolutional Neural Networks for detection

Using ensemble learning method Random Forests to classify styles and genres.


3
Prioritize
Importance
If each of these tasks could get done without any difficulty or cost, which would have the most positive impact?
Feasibility
Regardless of their importance, which tasks are more feasible than others? (Cost, time, effort, complexity, etc.)
+
-
-
+
Create a hierarchical CNN architecture in which the model first categorizes broad characteristics like art style, then in on specific details like objects or themes within artworks.
Use handcrafted features like color histograms, texture patterns, and shape descriptors to train Support Vector Machines (SVMs) to detect AI art.
Use pre-trained models (like ImageNet) and refine them for AI Art Detection.
Create a GANs to create synthetic artworks in particular styles, and use it to train a model to detect AI Art by differentiating between real and synthetic artworks.
Develop a hybrid model that combines the interpretability of SVMs with the feature learning capabilities of CNNs for AI Art Detection.
Combining CNNs, RNNs, and SVMs, to improve overall accuracy.
Use labeled datasets to train supervised learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs).
Using CNN to extract features from a labeled dataset and then using it for Detection.
Utilize large image datasets to train convolutional neural networks (CNNs) and fine-tune them for tasks related to art detection.
Utilize transfer learning with pre-trained Recurrent Neural Networks (RNNs) on sequential data.
Use recurrent neural networks or other time-series models to analyze the evolution of art styles and use it for AI Art Detection.
Develop an ensemble model combining the strengths of Support Vector Machines and Convolutional Neural Networks for detection
Use Transfer Learning using pretrained CNN models on a image dataset to improve detection.
Using RNN on a sequential dataset to understand authentic art.
Utilize pre-trained autoencoders to extract features from artworks, reducing dimensionality and capturing essential information for classification using machine learning models like SVM.
Using ensemble learning method Random Forests to classify styles and genres.

4. Project Design

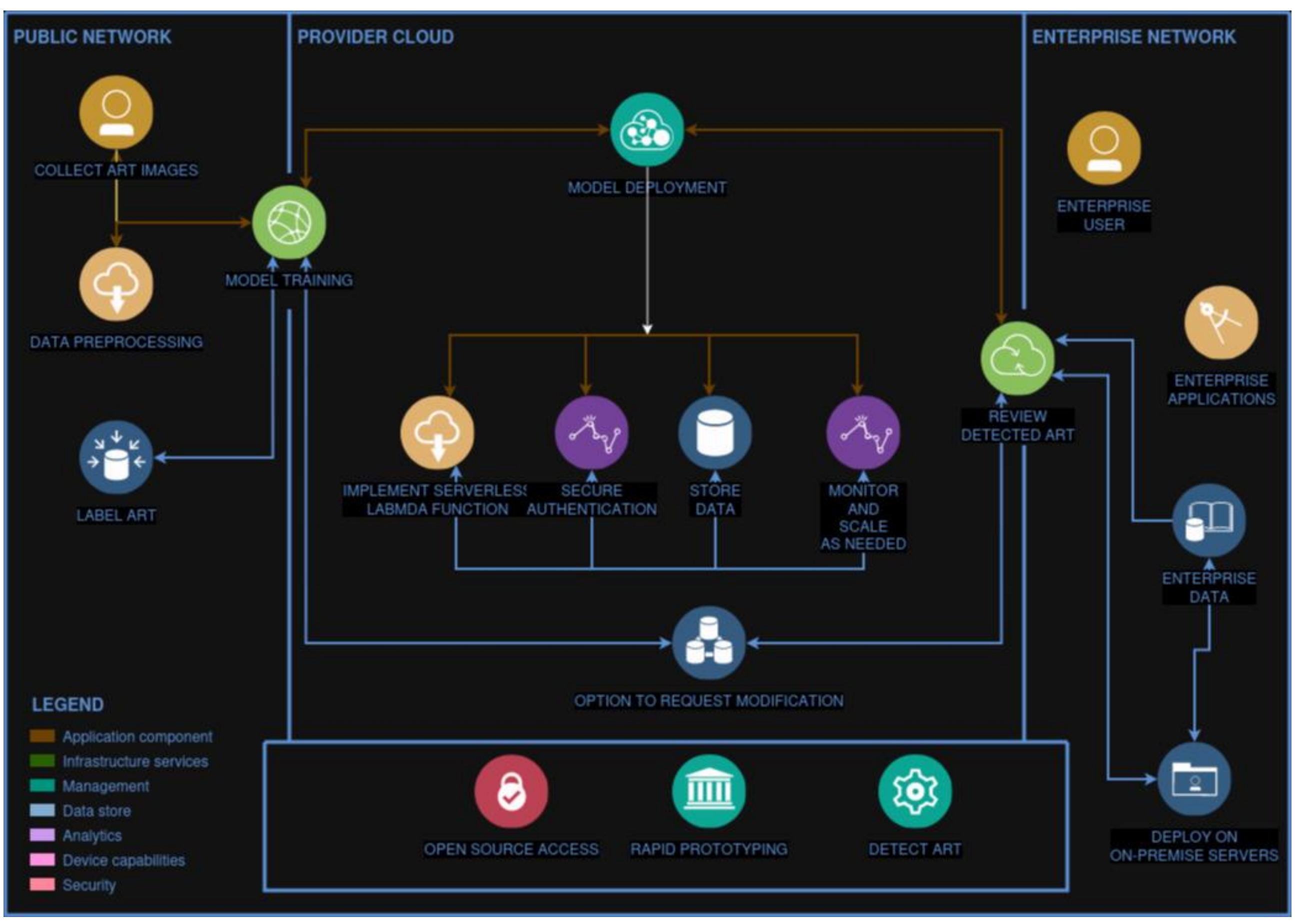
4.1 Data Flow Diagram



4.2 User Stories

User Type	Functional Requirement	User Story Number	User Story / Task	Acceptance criteria	Priority
Customer (Web user)	Uploading Image	USN-1	As a user, I can upload image in a particular image format	The system must validate and accept common image formats (e.g., JPEG, PNG).	High
		USN-2	As a user, I can get a analysis of the image	none	High
Art Collector	Upload Artwork for Analysis	USN-3	The Art Collector can upload an image file	The system must validate and accept common image formats (e.g., JPEG, PNG).	High
		USN-4	Upon successful upload, the system generates an analysis report with detected art style.		High
Administrator	Monitor performance	USN-5	As an administrator, I want to monitor system performance and usage	Generate reports	Medium

4.3 Solution Architecture



5. Project Planning and Scheduling

5.1 Technical Architecture

Table-1 : Components & Technologies:

S. No	Component	Description	Technology
1.	User Interface	It is how the user will be able to interact with the product.	CSS, React.
2.	Image Input	Uses a Graphical user interface to receive input.	Python using Flask, CSS, HTML
3.	Image Preprocessing	The Vector is processed and understood	Python, Keras, TensorFlow
4.	Deep Learning Model	A CNN Architecture that is used to extract features from the dataset.	Python, Keras, TensorFlow.
5.	GUI Display of results	Where the output of the model is displayed using the flask.	Python using Flask, CSS,React

Table-2: Application Characteristics:

S.No	Characteristics	Description	Technology
1.	Open-Source Usage	Uses Open Source frameworks to gather data to train and such.	python
2.	Scalable Architecture	Can be used as a microservice or a larger substantiated model which can be trained over the internet or a very isolated dataset.	Python, Keras, Tensorflow
3.	Availability	Available freely to people which can be powered by a minimal use of ads.	**null**
4.	Performance	Depending on the input the performance of the model will fluctuate, as a smaller isolated	Python, Keras, Tensorflow

		instance, the model can be expected to give much sooner than a larger dataset model.	

5.2 Sprint Planning & Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Image Input	USN-1	As a user, I can express my most desirable product	5	Medium	Smit
Sprint-2		USN-2	As a user, I can input my image into the website	5	Medium	Rishabh
Sprint-3	AI Image detection	USN-3	As a user, I can get the output as AI generated or not	5	High	Tharrun
Sprint-4	Dashboard - flask	USN-4	As a user, I can interact with the given application.	5	Medium	Anmol

5.3 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	3 Days	27 Oct 2023	29 Oct 2023	20	17 Nov 2023
Sprint-2	20	2 Days	30 Oct 2023	01 Nov 2023		
Sprint-3	20	10 Days	02 Nov 2023	11 Nov 2023		
Sprint-4	20	5 Days	12 Nov 2023	16 Nov 2023		

6. Coding and Solutioning

```
import tensorflow as tf

import os

from tensorflow import keras

import keras_preprocessing as kp

import cv2

import imghdr
```

Imported the necessary libraries.

```
data_scaled = data.map(lambda x,y :((x/255),y))
```

The data has been scaled by dividing each element by 255. This type of scaling is usually done for image dataset where pixel range is between [0,255] so by dividing by 255 the range is reduced to [0,1] making it suitable for neural network training.

```
train_size = int(len(data_scaled)*0.7)

val_size = int(len(data_scaled)*0.1)+1

test_size = int(len(data_scaled)*0.2)+1

train_size+val_size+test_size
```

Here the dataset is divided in 7:1:2 ration in which 70% of the dataset is for training, 10% of the dataset is for validation and 20% of the dataset is for testing

```
data_aug = tf.keras.Sequential(

   [

tf.keras.layers.experimental.preprocessing.RandomFlip("horizontal"),

      tf.keras.layers.experimental.preprocessing.RandomFlip("vertical"),
```

```
        tf.keras.layers.experimental.preprocessing.RandomRotation(0.4),

        tf.keras.layers.experimental.preprocessing.RandomZoom(0.5),

        tf.keras.layers.experimental.preprocessing.RandomContrast(0.2)

    ]

)

plt.figure(figsize=(10,10))

for images , _ in train.take(1):

    for i in range(9):

        augmented_images = data_aug(images)

        ax = plt.subplot(3,3,i+1)

        plt.imshow(augmented_images[0])
```

Here we have used data augmentation to increase the diversity of the training dataset. By using random flips (horizontal and vertical), random rotation, random zoom, and random contrast adjustments.

```
model = Sequential()

model.add(data_aug)


model.add(Conv2D(64, (3, 3), activation='relu'))

model.add(MaxPooling2D((2, 2)))


model.add(Conv2D(128, (3, 3), activation='relu'))

model.add(MaxPooling2D((2, 2)))

model.add(Dropout(0.2))
```

```
model.add(Conv2D(64, (3, 3), activation='relu'))

model.add(MaxPooling2D((2, 2)))

model.add(BatchNormalization())


model.add(Conv2D(128, (3, 3), activation='relu'))

model.add(MaxPooling2D((2, 2)))

model.add(Dropout(0.2))


model.add(Conv2D(128, (3, 3), activation='relu'))

model.add(MaxPooling2D((2, 2)))

model.add(BatchNormalization())


model.add(Conv2D(64, (3, 3), activation='relu'))

model.add(MaxPooling2D((2, 2)))


model.add(Flatten())

model.add(Dense(512, activation='relu'))

model.add(Dropout(0.5))

model.add(Dense(128, activation='relu'))

model.add(Dropout(0.5))

model.add(Dense(64, activation='relu'))
```

```
model.add(Dense(1, activation='sigmoid'))
```

Here the convolutional neural network is defined with 6 convolutional layers, 6 max pooling layers, 4 dropout layers, 2 batch normalization layers, 3 fully connected (dense) layers.

```
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

Here the model is compiled with adam optimizer, binary cross entropy and evaluation metrics.

```
hist = model.fit(train,epochs=20,validation_data=validation)
```

The model is trained for 20 epochs on the dataset while being monitored by the validation set.

```
def pred_img(img):

  im = cv2.imread(img)

  im = cv2.cvtColor(im, cv2.COLOR_BGR2RGB)

  resize = tf.image.resize(im,(256,256))

  yhat = model.predict(np.expand_dims(resize/255,0))

  if (yhat >= 0.5):

    plt.imshow(im)

    plt.title("Real")

  else:

    plt.imshow(im)

    plt.title("AI Generated")
```

After the model has been trained, if the prediction value is greater than 0.5 the image is real and if the prediction value is less than 0.5 the image is AI-Generated.

7. Performance Testing

7.1 Performance Metrics

Since the problem is of a binary classification nature, we are using binary cross-entropy to calculate the loss occurred whilst training the model. The training loss of the model can hence be calculated by the below formula

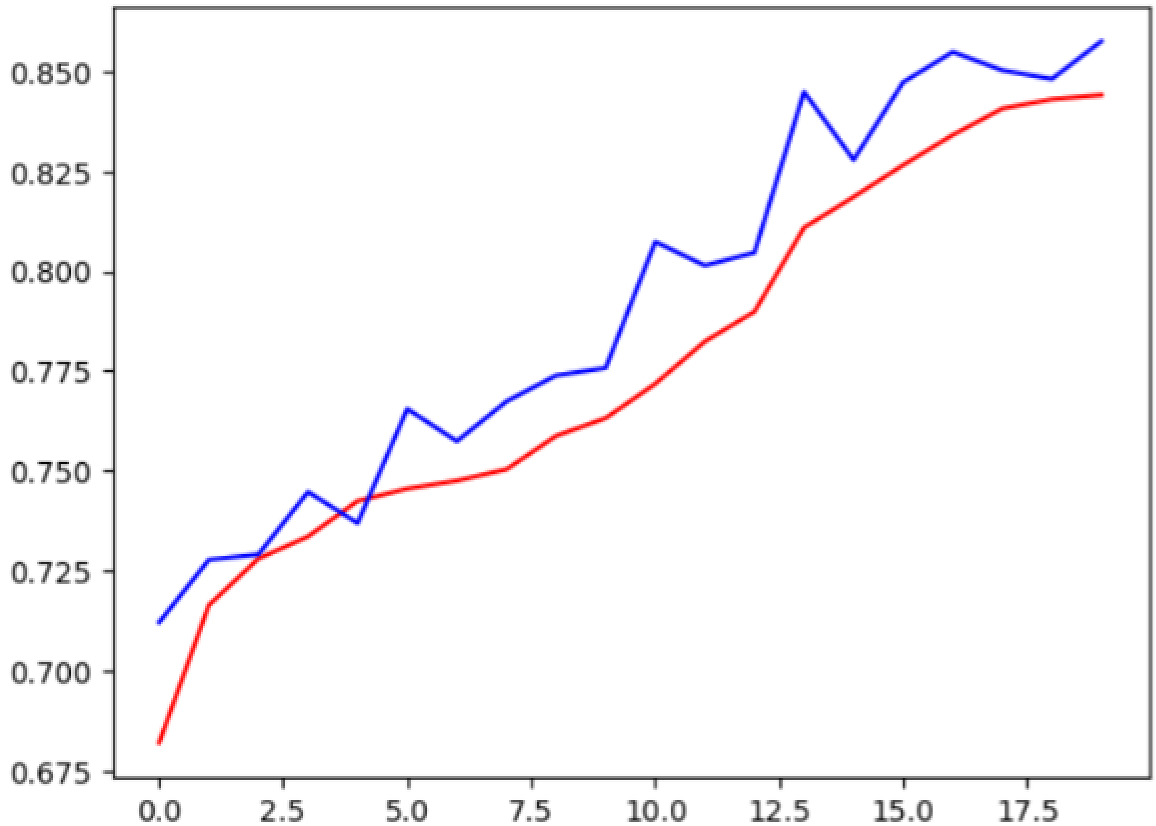
$$\text{Log loss} = \frac{1}{N} \sum_{i=1}^{N} -(y_i * \log(p_i) + (1-y_i) * \log(1-p_i))$$

y is the predicted where p is the true value.

And the accuracy similarly is measured by using binary accuracy calculations.

8. Results

The goal of the model is to be able to identify the probability of the Image fed to the model to be an AI-generated image. The model is trained on 620 batches per epoch with a total of 20 epochs. The validation accuracy of the model in the range of 2 – 10 is hovering around the range of 75 to 80 accuracy which indicates that the model is learning the data slowly but preventing overfitting of the data. Around the 10 – 19 epoch range we can see a significant rise in the rate of learning important data points as the accuracy of the validation is in the range of 80 to 87 with 87 being the best performance of the model. The blue line indicates the model when it is training on unseen data i.e. validation data whereas the red line indicates the model's accuracy in the proper classification of data that it is previously trained on i.e. training data.

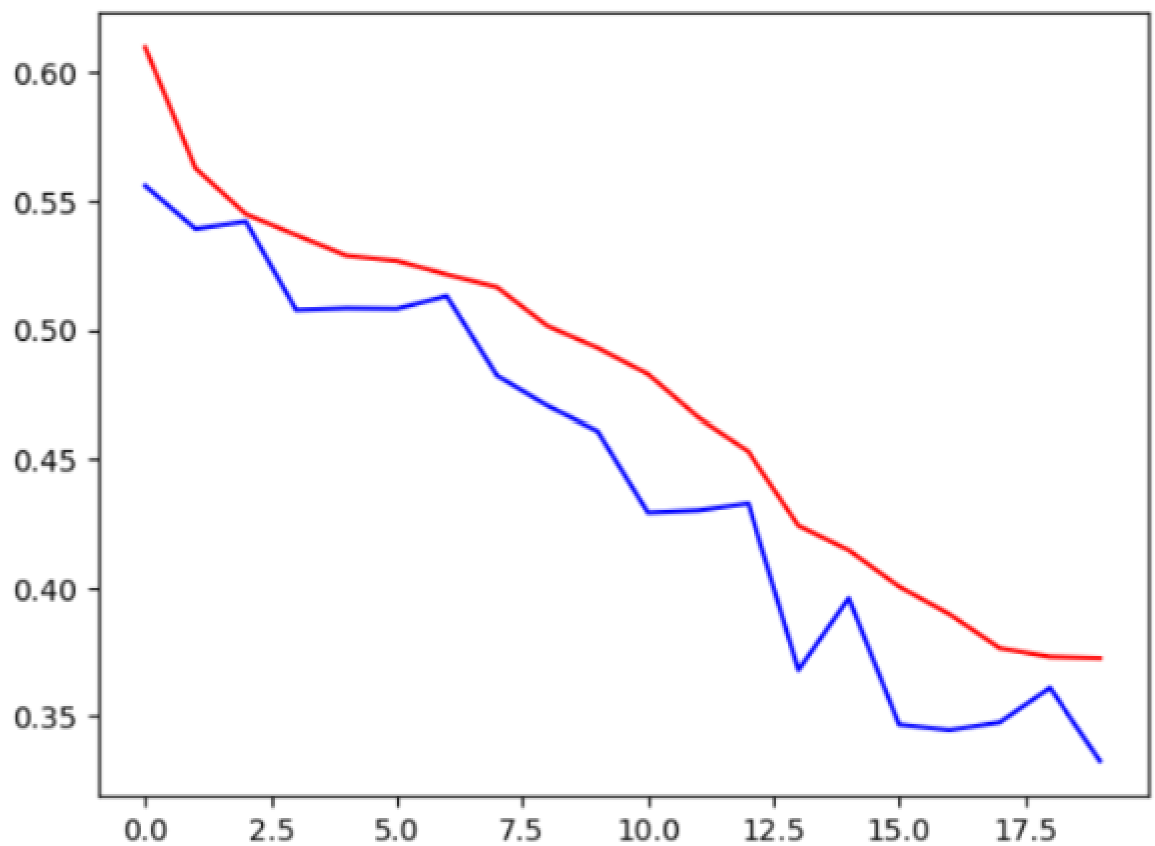


Empirically, accuracy seems like quite a limited measure of the quality of predictions. To predict whether a sample belongs to a class or not, our model outputs a number in the range of [0,1] where 0 or 1 being ground truth and ground false. To calculate accuracy, we take some arbitrary threshold (the most common being 0.5) to calculate whether the prediction is True or False. Since this threshold can be subject to change, accuracy can't be considered a correct or true indicator of the dataset

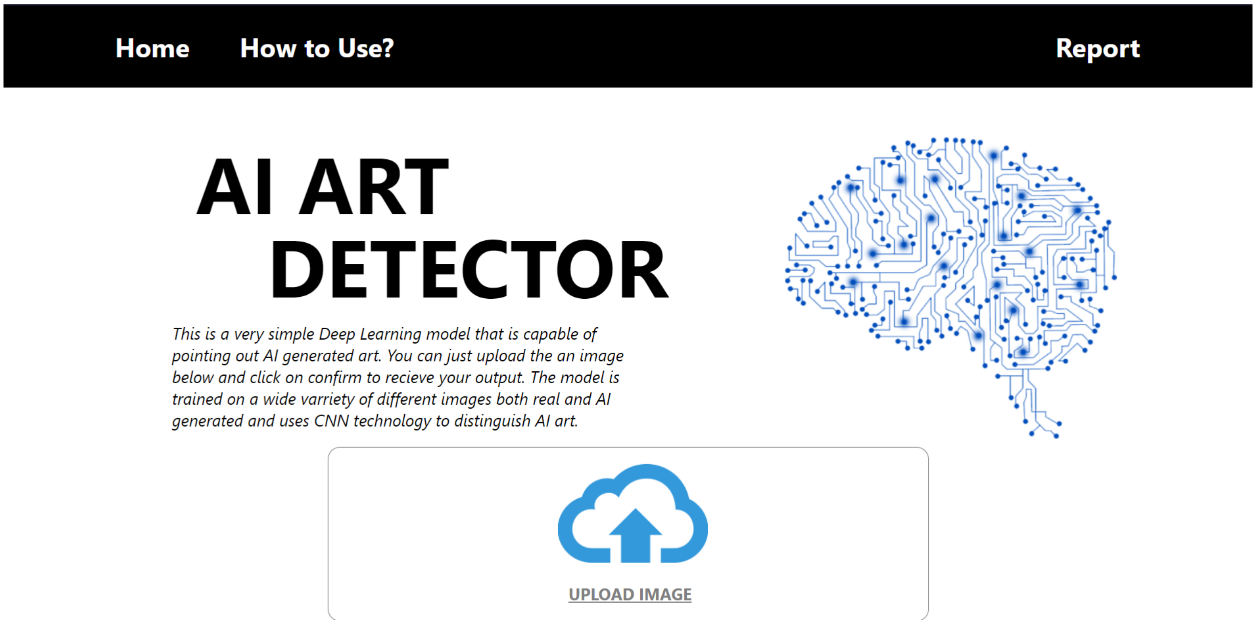
An accurate measure to check if the model is being trained properly is by observing the loss and validation loss or the loss that occurs due to predictions made on unseen data. If the Validation loss is increasing then there can be two major reasons for that. Either the model is cramming values(validation accuracy is decreasing) and not learning the data or there is some overfitting present(validation accuracy is increasing).

The model is trained on 620 batches per epoch with a total of 20 epochs. The validation loss of the model is not consistent and results in peaks during the training of the model.

This can be extrapolated for two reasons. The data set is not consistent such as unclear images or the model failing to see some major patterns in the dataset. The model Loss is a continuously decreasing slope from left to right indicating that the model is performing very well on the data that it can see and learn from. Since the problem does not lie in finding major patterns we can conclude that the spikes in the Validation loss is due to inconsistent data fed to the model.



8.1 Output Screenshots



9. Advantages and Disadvantages

CNN with augmentation is one of the most basic and most configurable types of Model present today. The model is completely open to customization to fit the need for a particular task. The Number of Convolutional layers is not specified and can be increased or decreased with regard to the performance of the model. Data augmentation is used before being fed to the model for evaluation. This prevents the model from overfitting and underfitting the data leading to improved accuracy. However, Due to its very customizable nature, a very deep understanding of the dataset is required in order to avoid overfitting or unnecessary computation. In some cases, it may require a very carefully implemented regularization technique.

CNN is a very robust mechanism to perform object detection from a given set of images and can be very powerful when the right parameters are set. Since the number of Convolutional Neural Networks are not predefined the outcome is very heavily dependent on the layers present. However this can sometimes cause the model to overfit and lose its accuracy. without the help of methods such as Data augmentation the only way to reduce overfitting will be using regularization techniques which can cause a loss of Data.

10. Conclusion

In this study, an analysis of a deep learning model called regular CNN was conducted for the detection and classification of Images based on if they were AI-generated or Real. Our investigation revealed nuanced differences in the performance of the model, shedding light on its strengths and limitations. Convolutional Neural Networks (CNN) have exhibited amazing performance in AI art detection, with an impressive accuracy rate of 87.5%. The ability of this technology to accurately identify and categorize art offers up fascinating possibilities for the art world and beyond. Artificial intelligence and art analysis together have wider applicability in many different fields and improve our knowledge of creative nuances.

The accomplishment of 87.5% accuracy denotes a substantial advance in automating the challenging process of art recognition. CNNs have shown to be a reliable option for this task thanks to their hierarchical feature extraction and pattern recognition skills. These networks have learned to discern the minute characteristics that set one artistic style apart from another by being trained on enormous archives of art images from various genres and eras. As a result, an automated tool that quickly recognizes and classifies artworks will be useful to art specialists, fans, and scholars, speeding up the study and categorization process.

11. Future Scope

Looking ahead, the potential and diversity of AI art identification utilizing CNN architecture are both encouraging. One way to advance is by making the precision even better. Even while 87.5 percent is an impressive accomplishment, the field is still developing, and researchers can work toward greater accuracy, possibly getting to the point where AI systems can match or even outperform human discernment. Additionally, the extension of the training dataset could result in more comprehensive art style detection, accepting lesser-known or underrepresented regional styles. The potential for AI-driven art history study is another fascinating direction. As CNN-based art identification algorithms develop, they may provide insightful information about the development of artistic styles and the factors that influenced them.

Additionally, the incorporation of AI art recognition into apps for virtual and augmented reality may completely alter how viewers experience art. Visitors to museums may have access to mobile devices that offer historical background, artist biographies, and stylistic analyses of the artwork they are witnessing. The effective implementation of CNN architecture in AI art detection with a 90% accuracy rate, in conclusion, marks a crucial turning point at the nexus of technology and art. For people all throughout the world, the future of this field holds the promise of ever-improving accuracy, improved art historical study, and life-changing artistic experiences. We set out on a journey that not only re-imagines how we see and understand art but also highlights the limitless potential of human-machine collaboration as we continue to harness the power of artificial intelligence.

12. Appendix

Source code

Source Code Link

Github and Project Demo Link

Git Hub Profile

Demo Link