

Research Proposal

by Sanjay Kumar Unkili

Submission date: 04-Mar-2026 12:42AM (UTC+0000)

Submission ID: 276400510

File name: 69339_Sanjay_Kumar_Unkili_Research_Proposal_726817_1754440493.pdf (1,006.95K)

Word count: 1906

Character count: 12557



Prifysgol Cymru
Y Drindod Dewi Sant
University of Wales
Trinity Saint David

Research Methods and Professional Development

ACFA7004

Project Title : Artistic Image Generation Using Neural Style Transfer

Sanjay kumar unkili

CONTENTS

- INTRODUCTION:
 - Objective of project
 - Scope of the project
- ANALYSIS:
 - Literature Survey
 - Problem Definition
 - Project Planning and Research
 - Software requirement specification
 - Software requirements
 - Hardware requirements
 - Model Selection and Architecture
- DESIGN:
 - Diagrams
 - Data Set Descriptions
 - Data Preprocessing Techniques
 - Methods & Algorithms
- References

INTRODUCTION

Objective of project

- To understand and implement Neural Style Transfer using deep learning techniques
- . To generate artistic images by blending content and style images.
- To utilize pre-trained CNN models to extract content and style features.

Scope of the project

- To develop a system that transforms a content image into an artistic image using neural style transfer.
- To use a pre-trained convolutional neural network to extract content and style features.
- To implement loss functions for content and style, and optimize an output image that balances both.

.

ANALYSIS:

➤ Literature Survey

- A systematic and thorough search of all types of published literature as well as other sources including dissertation, theses in order to identify as many items as possible that are relevant to a particular topic.
- Neural Style Transfer: A Critical Review” by A Singh 2021 Cited by 19 Neural Style Transfer (NST) is a class of software algorithms that allows us to transform scenes, change/edit the environment.
- Image Style Transfer Using Deep Learning Methods” by S Ren 2022-In this paper, we give an overview on current research progress and results of image style transfer using deep learning methods
- Image Style Transfer Based on VGG Neural Network Model” by Y Tao 2022 Cited by 8-The research results show that the use of the VGG-16 convolutional neural network to achieve image style transfer is better and more efficient.

Project Planning and Research

- Study foundational research papers on Neural Style Transfer, especially Gatys et al. (2015).
- Understand how CNNs are used to separate and combine content and style features.

❖ **Model Exploration**

- Analyze pre-trained CNN models such as Arbitrary image stylization.
- Study their layer architecture to identify suitable layers for content and style feature extraction.

❖ **Loss Function Design**

- Design content loss to preserve the structure of the original image.
- Design style loss using feature correlations to capture artistic patterns and colors.
- Combine both losses to control the balance between content and style.

Software requirement Specification

- Programming Language: Python
- Frameworks/Libraries: TensorFlow / PyTorch, Keras, NumPy, OpenCV, Matplotlib
- IDE: Jupyter Notebook / VS Code
- Operating System: Windows / Linux

Hardware requirements

- Processor: Intel i5 or higher
- RAM: Minimum 8 GB
- Storage: 10 GB free space

Model Selection and Architecture

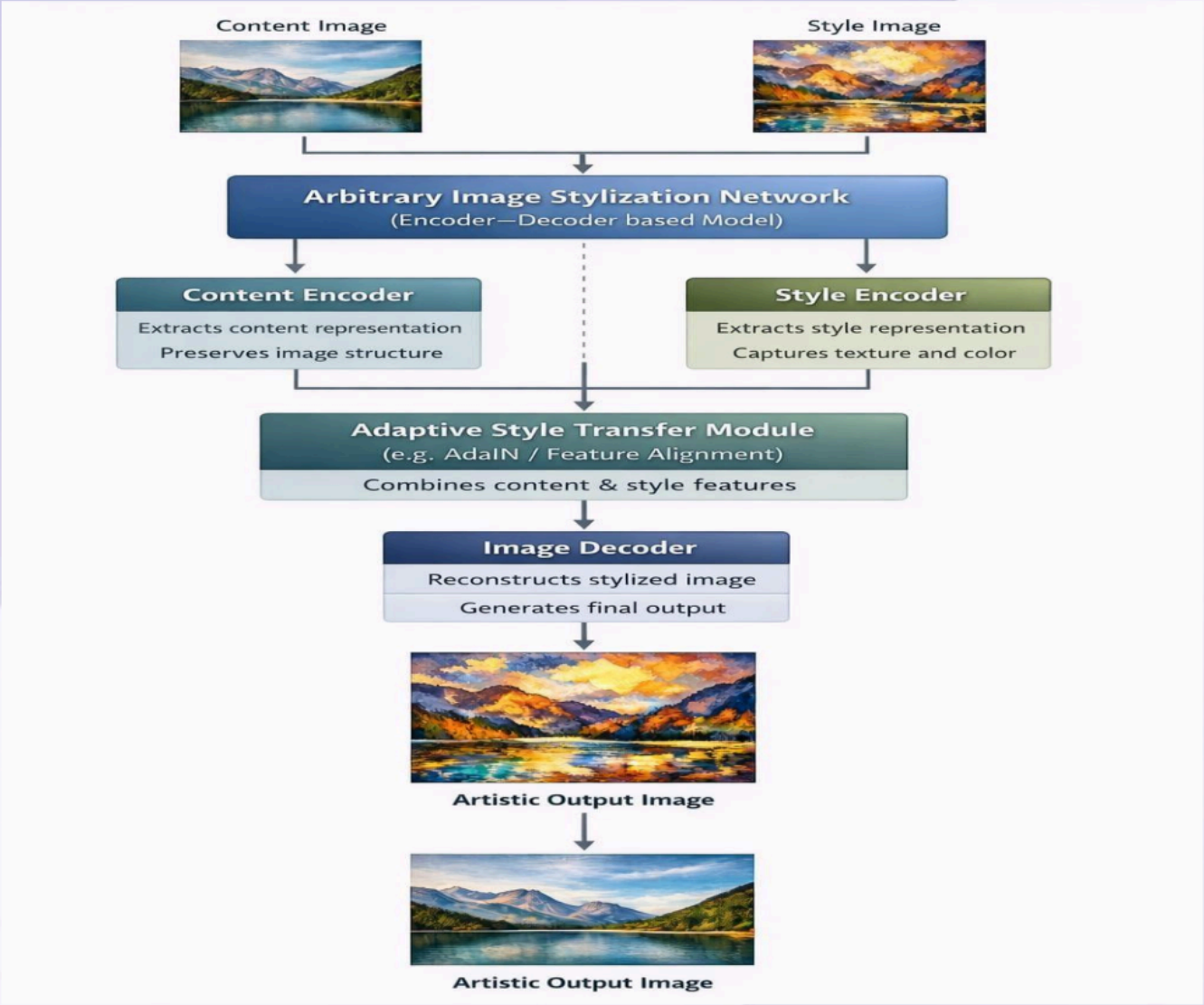
Base Model: Arbitrary image stylization

- Arbitrary image stylization uses a single model to apply any unseen style without retraining.
- It is fast and efficient due to feed-forward inference.
- The method is practical for real-time and scalable applications.
- It delivers stable, visually pleasing results and is widely accepted in research.

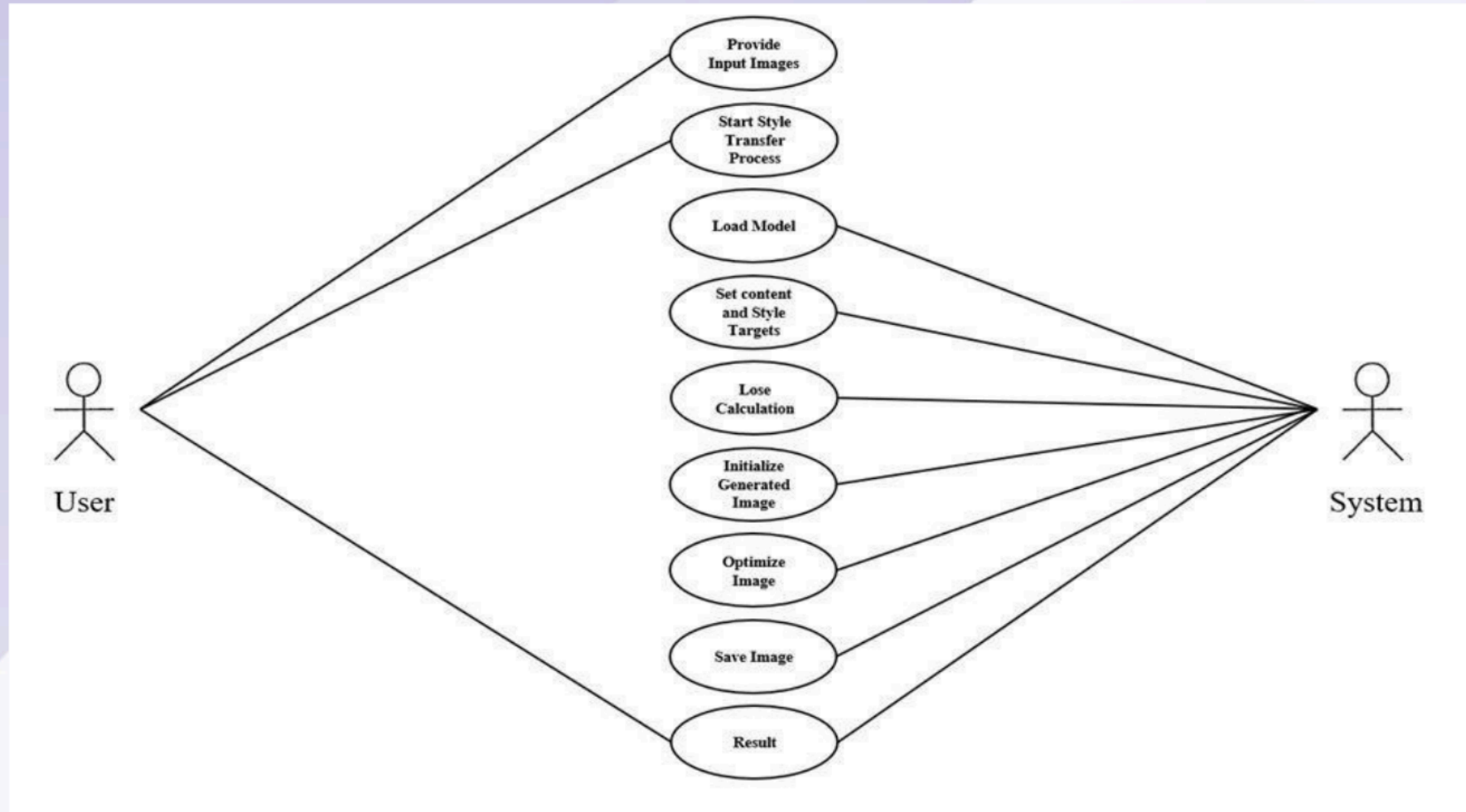
Content Representation

- Content representation captures the structure and spatial layout of an image.
- It preserves the original image content during stylization.

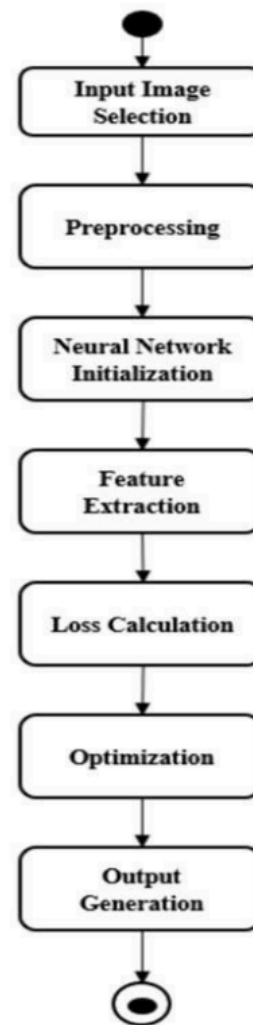
Architecture



DESIGN: Use-Case Diagram



Activity diagram:



Data Set Description

- Uses **image data** as input
- Two inputs:
 - **Content Image** – provides structure
 - **Style Image** – provides artistic patterns
- Image formats: **JPG / PNG**
- Images are **resized and normalized** before processing
- No labeled dataset required (unsupervised learning)
- Output is a stylized artistic image

Data Preprocessing Techniques

- **Image Selection** – Choose content and style images (JPG/PNG)
- **Image Resizing** – Resize images to a fixed size for Arbitrary image stylization
- **Pixel Normalization** – Normalize pixel values as per model requirements
- **Mean Subtraction** – Subtract ImageNet mean for Arbitrary image stylization compatibility
- **Tensor & Batch Conversion** – Convert images to tensors and add batch dimension

Methods & Algorithms

Neural Style Transfer (NST) Technique

Used to blend the content of one image with the artistic style of another image.

Pre-trained Arbitrary image stylization Feature Extraction

A arbitrary image stylization CNN model is used to extract deep visual features from both content and style images.

Content Representation & Content Loss

Content features are taken from deeper layers, and content loss ensures the generated image preserves structure and objects.

Style Representation using Gram Matrix

Style features are captured using Gram matrices to represent textures, patterns, and color styles.

Total Loss Optimization

A weighted combination of content loss and style loss is computed to balance structure and artistic appearance.

Gradient Descent–Based Image Optimization

The generated image is iteratively updated using backpropagation and gradient descent until the total loss is minimized.

REFERENCES

- [1] C. Ma, Z. Sun, and C. Ruan, “ Style creation: multiple styles transfer with incremental learning and distillation loss,” 2024.
- [2] S. Nath P and R. Chouhan, “Quantifying image naturalness using transfer learning and fusion model,” 2024. [3] D. Li and W. Gao, “ Neural style transfer based on deep feature synthesis,” 2023.
- [4] X. Yu and G. Zhou, “ ECM: arbitrary style transfer via enhanced-channelmodule,” 2023.
- [5] X. Wang, Y. Lyu, J. Huang, Z. Wang, and J. Qin, “Interactive artistic multi-style transfer,” 2021.
- [6] SPAST: Arbitrary Style Transfer with Style Priors via Pre-trained Large-scale Mode(2025)
- TZhang, [HTang](#) - arXiv preprint arXiv:2506.19278, **2025** - arxiv.org

Title: Artistic Image generation using Neural Style Transfer

Abstract

Neural Style Transfer (NST) is a deep learning technique that generates artistic images by combining the content of one image with the style of another. This work presents an artistic image generation system using an arbitrary style transfer model based on a pre-trained Convolutional Neural Network, specifically VGG19. Unlike traditional methods that require retraining for each new style, the proposed approach supports multiple unseen styles with efficient feed-forward inference. Content and style features are extracted from different network layers, and an optimized loss function balances content preservation and artistic appearance. Experimental results demonstrate visually pleasing stylized images while maintaining structural integrity, highlighting the effectiveness of neural style transfer in creative and digital art applications.

Keywords

Neural Style Transfer, Arbitrary Stylization Model, Deep Learning, Convolutional Neural Network, VGG19.

Introduction

Neural Style Transfer (NST) is a deep learning technique that enables the generation of artistic images by combining the content of one image with the style of another. It leverages Convolutional Neural Networks (CNNs) to extract and separate content and style representations from different layers of a pre-trained network. In recent years, NST has gained significant attention due to its applications in digital art, visual media, and creative design. Traditional style transfer methods are often limited to a single artistic style and require retraining for each new style, making them computationally expensive and less scalable. To address these limitations, this work adopts an arbitrary style transfer model

based on a pre-trained CNN, specifically VGG19, which allows multiple unseen styles to be applied without retraining. By optimizing content loss and style loss, the proposed approach generates visually appealing artistic images while preserving the structural integrity of the content image, demonstrating the effectiveness of deep learning in creative image generation.

Literature Review

Neural Style Transfer (NST) has been extensively explored to enhance artistic image generation by effectively separating and recombining content and style representations. Early CNN-based approaches such as SAFIN introduced self-attention and advanced normalization techniques to capture global style patterns while preserving content structure, though with increased computational overhead [1]. Contrastive learning-based models improved content-style disentanglement and visual consistency across diverse styles but required complex training procedures and high-quality samples [2]. Aesthetic-aware and affinity-based attention networks further enhanced visual quality and fine-grained content preservation, at the cost of higher memory usage and longer inference time [3], [4]. Recent hybrid CNN-Transformer architectures improved global context modeling and style distribution consistency but significantly increased computational complexity [5]. Other works focused on controllable and object-aware style transfer, enabling fine-grained stylization and semantic control, yet relied on costly optimization or accurate segmentation models [6]. Creative permutation-based approaches explored expressive stylization but sometimes compromised structural consistency [7]. These studies reveal a trade-off between stylization quality, control, and efficiency, motivating the adoption of an arbitrary style transfer approach that supports multiple unseen styles without retraining while maintaining stable performance.

Problem Statement

Existing Neural Style Transfer methods often suffer from high computational complexity, increased memory usage, and limited scalability. Many approaches require retraining for new artistic styles, complex optimization during inference, or additional preprocessing such as object segmentation, making them unsuitable for real-time and flexible applications. Therefore, there is a need for an efficient and scalable style transfer approach that can handle multiple unseen styles without retraining while preserving content structure and producing high-quality artistic results.

Proposed Methodology

The proposed system is based on an arbitrary neural style transfer framework that generates artistic images by combining a content image and a style image using deep learning techniques. A pre-trained Convolutional Neural Network, specifically VGG19, is used as a feature extractor to capture hierarchical representations of both content and style images. Content features are extracted from deeper layers to preserve structural information, while style features are extracted from multiple layers to capture textures, patterns, and colour distributions. The generated image is optimized by minimizing a weighted combination of content loss and style loss, ensuring a balance between content preservation and artistic stylization. The arbitrary stylization approach enables the application of multiple unseen styles without retraining the model, making the system efficient and scalable.

Implementation Details

The system is implemented using Python with deep learning frameworks such as TensorFlow or PyTorch. The pre-trained VGG19 network is utilized for feature extraction, and images are processed in standard formats such as JPG and PNG. Prior to processing, input images are

resized and normalized according to model requirements. The implementation computes content loss to preserve spatial structure and style loss using Gram matrix representations to capture artistic patterns. Gradient-based optimization is applied to iteratively update the generated image until the total loss is minimized. The experiments are conducted on a system with a minimum of 8 GB RAM and an Intel i5 or higher processor, ensuring efficient execution and stable results.

Results and Discussion

The experimental results demonstrate that the proposed arbitrary neural style transfer model successfully generates high-quality artistic images while preserving the structural integrity of the content image. The system effectively transfers textures, patterns, and colour schemes from the style image to the content image without noticeable distortion. Compared to traditional single-style transfer methods, the proposed approach provides greater flexibility by supporting multiple unseen styles without retraining. The results confirm that deep neural networks can efficiently balance artistic appearance and content preservation, making the approach suitable for creative and real-time applications.

Advantages

- Supports multiple unseen artistic styles without retraining
- Efficient feed-forward inference suitable for real-time applications
- Preserves content structure while achieving high-quality stylization
- Scalable and flexible compared to traditional NST methods

Limitations

- Limited fine-grained control over individual style elements
- Performance depends on the quality of the pre-trained model

- High-resolution images may increase processing time

Future Work

Future enhancements may include extending the system to video style transfer while maintaining temporal consistency. Additional user controls for adjusting style intensity and content preservation can be incorporated. The model can also be optimized for deployment on mobile and edge devices. Integrating transformer-based architectures or generative adversarial networks may further improve stylization quality and creative diversity.

Conclusion

This work demonstrates the effectiveness of Neural Style Transfer for artistic image generation using an arbitrary stylization model. By leveraging a pre-trained CNN for feature extraction, the system successfully blends content and style images while supporting multiple unseen styles without retraining. The results show that the proposed approach maintains content structure and achieves visually appealing artistic outputs with improved efficiency and scalability. This highlights the potential of deep learning techniques in creative applications such as digital art, media, and visual design.

References

- [1] H. Park and J. Lee, "SAFIN," *ICCVW*, 2021.
- [2] Y. Liu et al., "Unified Style Transfer via Adaptive Contrastive Learning," *IEEE TIP*, 2023.
- [3] Z. Chen et al., "AesFA," *Pattern Recognition*, 2023.
- [4] J. Kim et al., "AeANet," *IEEE TMM*, 2024.
- [5] X. Wu et al., "Rethinking Style Transfer with Transformers," *CVPR*, 2024.
- [6] L. Wang et al., "Controllable Style Transfer via INR," *IEEE TVCG*, 2024.
- [7] P. Kumar and A. Verma, "Object-Aware NST," *CVIU*, 2024.
- [8] T. Zhang et al., "Creative Style Transfer via Neural Permutation Networks," *arXiv*, 2025.

Research Proposal

GRADEMARK REPORT

FINAL GRADE

GENERAL COMMENTS

21 /100

Further to the comments provided during the presentation,
please follow the feedback provided for each category in the rubric.

The proposed topic is not relevant to the area of study. So please change the topic as discussed.

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

GRADING FORM: ACFA7004 PROPOSAL PRES 2026

ENGAGEMENT WITH LIT.SKILL [20]

Relevant and recent Literature support for Research background/context [7 Marks] Recent Literature support for the identified research problem [7 Marks] Recent and Relevant in-text citations and reference list [6 Marks]

 The content provided is not relevant to the area of study. Need to understand the elements of research such as literature review, citation and referencing,

4

KNOWLEDGE _ UNDER.. SKILLS[15]

Brief overview and current developments in the proposed research area [10 Marks] Research problem statement [5 Marks]

 Please refer to the comments provided during the presentation.

2

COGNITIVE&INTELL. SKILLS[20]

Formulation of research aim and objective based on the identified research problem [20 Marks]

 Need to formulate new research aim and objectives. 0

PRACTICAL APPN SKILLS[25]

*Selection of appropriate research methods and materials to achieve the research objectives, with justification [15 Marks]
Details of the data collection and evaluation process [10 Marks]*

 Understand research methods and research design and prepare the research methodology that aligns with the the research objectives. 5

TRANSF. SKILL & PROF.PRAC [20]

Project planning and resource management [10 Marks] Description of the project’s potential impact and limitations [5 Marks] Presentation style [5 Marks]

 Understands project planning and uses a tool to provide the project timeline. Presentation style was good, though the proposed topic is not acceptable. 10