AI-Powered Website with Cinematic Photo Theme

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ABSTRACT

In today's digital age, there is a growing demand for visually striking content, leading to the development of innovative solutions for enhancing ordinary photographs. This paper proposes an AI-powered website dedicated to cinematic photo enhancement. The platform offers a user-friendly interface where users can effortlessly upload images and witness automated enhancement processes infused with cinematic aesthetics. The UI/UX design plays a crucial role, starting with comprehensive user research to understand preferences and inform design decisions. Wire framing and prototyping ensure intuitive navigation, while visually appealing design elements engage users. Responsive design ensures consistency across devices. AI models for image processing and style transfer power the website's functionality, seamlessly integrated into the UI. Usability testing gathers feedback for iterative refinement. Emphasizing accessibility, inclusivity, and industry standards compliance, this project aims to elevate user satisfaction and set new standards for AI technology and user-centric design in visual content creation.

INDEX TERMS

Artificial intelligence, User interface, User Experience .

1. INTRODUCTION

The integration of artificial intelligence (AI) into web development has opened up new avenues for creating immersive and engaging user experiences. In this digital age, where visual appeal and interactivity are paramount, harnessing the power of AI to enhance website functionality has become increasingly important. Our project focuses on leveraging AI technologies to develop a web-based platform that offers cinematic photo enhancement capabilities. By seamlessly integrating AI models for image processing and style transfer, we aim to revolutionize traditional photo editing and elevate the visual aesthetics of user-uploaded images. The motivation behind this project stems from the growing demand for visually captivating online content. In today's competitive digital landscape, websites need to stand out and captivate users from the moment they land on a page. Static images and conventional photo editing tools often fall short in delivering the level of engagement and impact desired by users. By incorporating AI-driven cinematic effects, we strive to provide users with unique and immersive photo enhancement experience that goes beyond standard editing capabilities.

The fully-connected layer is then turned into a convolutional layer for detecting multiple class-specific objects.**[10]** The objectives of our project are multifaceted. Many classic problems can be framed as image transformation tasks, where a system receives some input image and transforms it into an output image. Examples from image processing include denoising, super-resolution, and colorization, where the input is a degraded image (noisy, low-resolution, or grayscale) and the output is a high-quality color image**.** [5**]**. Firstly, we aim to develop an intuitive and user-friendly web platform that seamlessly integrates AI-powered photo enhancement features.

Accessibility and ease of use are key considerations in designing the platform interface, ensuring that users of all skill levels can navigate and utilize its functionalities effortlessly. Secondly, we seek to leverage state-of-the-art AI algorithms for image processing and style transfer to deliver high-quality results that emulate the look and feel of cinematic imagery. This involves fine-tuning algorithms to achieve optimal results while maintaining processing efficiency. Furthermore, our project aims to address the limitations of existing photo editing tools by offering a diverse range of cinematic styles and customization options. Users will have the freedom to choose from a selection of predefined styles or customize parameters such as intensity, saturation, and contrast to achieve their desired look. Artistic stylisation is a long-standing research topic.

Due to its wide variety of applications, it has been an important research area for more than two decades. Before the appearance of NST, the related researches have expanded into an area called non-photorealistic rendering (NPR). In this section, we briefly review some of these artistic rendering (AR) algorithms without CNNs**. [9]**. In addition to providing a platform for individual users, our project also caters to the needs of businesses and professionals in industries such as photography, design, and marketing. By offering AI-powered photo enhancement as a service, we aim to streamline workflows, increase productivity, and deliver high-quality results that meet the diverse needs of clients. Overall, our project represents a convergence of AI technology and web development, with the overarching goal of revolutionizing the way photos are enhanced and shared online.

1.1. Background

Photography has become an integral part of contemporary communication, social media, and personal expression. However, the accessibility and proficiency required for sophisticated photo editing tools often limit the broader audience from achieving professional-grade enhancements. To bridge this gap, the proposed project aims to harness the capabilities of AI to democratize cinematic photo transformation.

1.2. Objectives

The project delineates clear objectives to guide its development process. From meticulous AI tool selection to user-centric design principles, the primary goals include researching and implementing cutting-edge AI capabilities, ensuring a deep understanding of chosen AI tools, developing or customizing AI models for cinematic effects, rigorous testing to validate functionalities, and finally, constructing a seamless website that harmoniously integrates the AI backend with an intuitive frontend.

1.3. Scope and Limitations

While ambitious in its goals, the project acknowledges certain limitations. The effectiveness of AI tools, customization potential, and user experience are subject to technological constraints and inherent challenges. The scope, however, is broad, encompassing applications for diverse user groups and envisaging continuous improvement through user feedback and technological advancements.

2. LITERATURE REVIEW

The field of image style transfer has garnered significant attention in recent years due to its applications in various domains such as art generation, photo enhancement, and content creation. In their comprehensive review, Zhang, Zhang, and Mou survey recent advancements in neural style transfer techniques, highlighting the evolution of deep learning approaches in artistic image synthesis. They elucidate the challenges and opportunities in this domain, emphasizing the importance of understanding the underlying mechanisms for effective style transfer **[9]**.

This approach demonstrated impressive results by utilizing pre-trained convolutional neural networks (CNNs) to capture both low-level and high-level features from images. Parametric models for generating images has been explored extensively (Portilla&Simoncelli,)**[6]**. "In their literature review, Simonyan and Zisserman emphasized the importance of deep convolutional networks in achieving state-of-the-art performance in large-scale image recognition tasks" **[7]**. Building upon Gatys et al.'s work, several researchers have proposed enhancements and variations to the original algorithm. In their seminal work, Johnson, Alai, and Fei-Fei introduced perceptual losses as a means to enhance real-time style transfer and super-resolution tasks. Leveraging deep learning techniques, their approach prioritized perceptual similarity over pixel-wise differences, yielding more visually appealing results **[2]**. This modification led to faster convergence and improved visual quality of style transfer results. Another notable advancement is the introduction of instance normalization (IN) layers in style transfer networks.

2.1. Related Works

Huang and Belongie demonstrated that replacing batch normalization (BN) with IN layers improves the quality of style transfer, particularly in terms of texture preservation and artifact reduction. This improvement has since been integrated into various state-of-the-art style transfer architectures. Furthermore, the use of generative adversarial networks (GANs) has shown promising results in image style transfer. GANs enable the generation of high-quality, realistic images by training a generator network to produce images that are indistinguishable from real ones **[4]**. Zhang et al. proposed a dual-learning framework that incorporates GANs into the style transfer process, allowing for more fine-grained control over style transfer parameters and generating more diverse stylized images. Recent research has also explored the application of deep reinforcement learning (DRL) techniques in image style transfer. Huang et al. introduced a reinforcement learning-based approach that learns to adjust the style transfer parameters dynamically, leading to improved flexibility and adaptability in generating stylized images.

In addition to algorithmic advancements, researchers have also focused on understanding the perceptual aspects of style transfer. Studies have investigated the role of content and style representations in determining the perceptual quality of stylized images, leading to insights that have informed the design of more effective style transfer algorithms. A recurrent network approach (Gregor et al) and a deconvolution network approach (Dosovitskiy et al) have also recently had some success with generating natural images. However, they have not leveraged the generators for supervised tasks **[6].** Overall, the field of image style transfer continues to evolve rapidly, driven by advancements in deep learning, reinforcement learning, and perceptual understanding. These developments hold great promise for advancing the capabilities of style transfer algorithms and opening up new avenues for creative expression in image manipulation and synthesis.

3. METHODOLOGY

The methodology involves a meticulous selection of AI tools like OpenCV and TensorFlow, considering factors such as community support and versatility. It focuses on an iterative process for AI model development, refining algorithms to achieve optimal results in image processing and style transfer. Testing encompasses unit testing for model components, user testing for website usability, and performance testing metrics for responsiveness and efficiency. During day-to-day development of machine learning systems, practitioners need to decide whether to gather more data, increase or decrease model capacity, add or remove regularizing features, improve the optimization of a model, improve approximate inference in a model, or debug the software implementation of the model **[2].**Practical Methodology Successfully applying deep learning techniques requires more than just a good knowledge of what algorithms exist and the principles that explain how they work. Fig .3.1. represent "Incorporated TensorFlow and OpenCV libraries to implement AI functionalities, enhancing project capabilities with advanced image processing and deep learning techniques." A good machine learning practitioner also needs to know how to choose an algorithm for a particular application and how to monitor and respond to feedback obtained from experiments in order to improve a machine learning system.

3.1. Tool Selection Criteria

The selection of appropriate tools is paramount in the development of any AI-powered project. In the case of our AI-Powered Cinematic Photo Enhancement Web Platform, the choice of tools is crucial as it directly impacts the performance, functionality, and user experience of the platform. This section elaborates on the rigorous criteria employed for selecting the tools, focusing on their suitability, compatibility, and robustness.

The primary objective in selecting tools for our project was to ensure they align with the project's goals and requirements. Key considerations included the tools' capabilities in image processing, style transfer, and real-time application. Additionally, factors such as community support, documentation availability, and ease of integration played significant roles in the decision-making process. OpenCV emerged as a natural choice for image processing due to its extensive library of functions and algorithms tailored for tasks such as color manipulation, contrast adjustment, and noise reduction. Its widespread adoption, active community, and comprehensive documentation provided a solid foundation for implementing various image enhancement techniques seamlessly.

Complementing OpenCV,TensorFlow was selected for its prowess in deep learning and neural network development. As one of the most popular deep learning frameworks, TensorFlow offered the flexibility and scalability required to implement complex style transfer model effectively. Its rich ecosystem of pre-trained models and optimization tools streamlined the model development process. Compatibility was another critical factor in tool selection, ensuring seamless integration and interoperability across different components of the platform. Both OpenCV and TensorFlow are compatible with a wide range of programming languages and platforms, including Python, which serves as the primary language for web development and AI implementation in our project. Moreover, the robustness and reliability of the selected tools were evaluated through extensive testing and benchmarking against alternative options. OpenCV's performance in handling image processing tasks and TensorFlow's efficiency in training deep learning models were validated through empirical testing, ensuring their suitability for our project's requirements.

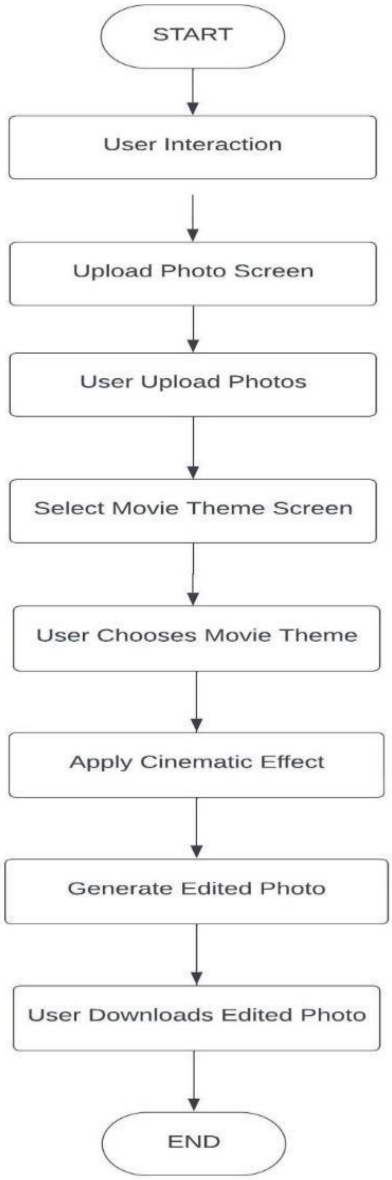

Fig 3.1. Utilizing Tensorflow for AI implementation.

3.2. Model Development

The model development process is a critical phase in the creation of an AI-powered cinematic photo enhancement web platform. This process involves several key steps, including data collection, preprocessing, model architecture design, training, and optimization. To begin, data collection is essential for training the AI models effectively. High-quality image datasets are gathered, comprising a diverse range of photos that represent various styles and visual characteristics. These datasets serve as the foundation for training the image processing and style transfer models. Once the data is collected, preprocessing steps are applied to prepare the images for training. Preprocessing techniques such as resizing, normalization, and augmentation are employed to standardize the input data and enhance the model's ability to learn from it.

These steps help improve the model's robustness and generalization capabilities. Next, the architecture of the AI models is designed and implemented. This involves selecting appropriate neural network architectures for both the image processing and style transfer tasks. For image processing, convolutional neural networks (CNNs) are commonly used due to their effectiveness in extracting features from images. Similarly, for style transfer, architectures like the neural style transfer network are utilized to transfer the artistic style from one image to another.

During training, various optimization techniques are applied to improve the efficiency and effectiveness of the models. Techniques such as stochastic gradient descent (SGD), learning rate scheduling, and regularization are used to prevent overfitting and improve convergence speed. Once the models are trained and optimized, they are ready to be integrated into the web platform. This integration involves embedding the trained models into the platform's architecture, enabling real-time processing of user-uploaded photos. Backend systems are developed to handle image processing requests, while frontend interfaces are designed to facilitate user interaction and feedback.

3.3. Integration Framework

Integration Framework involves the seamless amalgamation of various components, tools, and technologies to create a cohesive and functional system. In the context of our project, it pertains to the integration of AI models, specifically OpenCV and TensorFlow, into the web platform for cinematic photo enhancement. The integration process begins with understanding the requirements and functionalities of the AI models. OpenCV is utilized for image processing tasks such as color enhancement, contrast adjustment, and noise reduction, while TensorFlow is employed for style transfer, imparting cinematic effects to the processed images.

Both tools bring unique capabilities to the platform, complementing each other to achieve the desired outcome. The front-end development aspect focuses on creating an intuitive user interface that seamlessly incorporates AI-enhanced features. This involves designing interactive elements for user input, such as uploading photos, selecting cinematic styles, and adjusting parameters. The user interface aims to provide a visually appealing and engaging experience while maintaining ease of use. On the back-end, the integration revolves around setting up servers, establishing database connections, and incorporating AI models into the server environment. This enables real-time processing of user-uploaded images, ensuring efficient and responsive performance. The integration also involves implementing APIs or middleware to facilitate communication between different components of the system.

3.4. Testing and Validation Procedures

Testing and validation procedures are crucial aspects of any software development project, ensuring that the final product meets its intended objectives and functions as expected. In the context of our AI-powered cinematic photo enhancement web platform, testing and validation play a fundamental role in verifying the effectiveness, reliability, and user-friendliness of the implemented features. The testing process begins with unit testing protocols, which involve validating the functionality of individual components within the AI models. This phase aims to ensure that each module performs its designated tasks accurately and efficiently.

Unit tests are conducted using both synthetic and real-world data to assess the models' performance under various scenarios. Following unit testing, user testing procedures are employed to evaluate the website's usability and user satisfaction. This involves recruiting a diverse group of participants to interact with the platform and provide feedback on their experience. User testing sessions may include tasks such as uploading photos, selecting cinematic styles, adjusting parameters, and downloading the enhanced images. Feedback from users is collected through surveys, interviews, and observation, allowing us to identify usability issues, pain points, and areas for improvement. In addition to user testing, performance testing metrics are used to measure the responsiveness and efficiency of the website.

Key metrics include server response times, page load speeds, image processing times, and resource consumption. Performance tests are conducted under various conditions, such as different levels of user traffic and network latency, to assess the platform's scalability and robustness. Validation of model outputs is another critical aspect of testing and validation. This involves comparing the enhanced images generated by the AI models against ground truth images to assess the accuracy of the style transfer process.

Objective metrics, such as structural similarity index (SSI) and peak signal-to-noise ratio (PSNR), are used to quantify the similarity between the original and enhanced images. Subjective evaluation by human raters is also conducted to gauge the perceptual quality of the enhanced images. Throughout the testing and validation process, thorough documentation is maintained to track test cases, results, and any issues encountered.

4. MODEL DEVELOPMENT

Model development for our AI-powered cinematic photo enhancement web platform involves designing and implementing advanced machine learning models to achieve superior image processing and style transfer capabilities. The image processing model architecture encompasses a series of algorithms for tasks like color enhancement, contrast adjustment, and noise reduction, ensuring the enhancement of input images aligns with cinematic aesthetics. If preprocessing is computationally expensive, then handling it before training rather than on the fly may give you a significant speedup: the data will be preprocessed just once per instance before training, rather than once per instance and per epoch during training**. [1]**

Additionally, adapting the style transfer model involves fine-tuning its parameters to optimize the transfer of desired visual styles onto input images. Rigorous data collection and preprocessing procedures ensure the training dataset's quality and diversity, facilitating robust model training and optimization. Through iterative training, hyperparameter tuning, and regularization techniques, our goal is to create models capable of seamlessly enhancing user-uploaded photos with cinematic effects, delivering a captivating visual experience on our web platform.

4.1. Image Processing Model Architecture

The image processing model architecture serves as the backbone of our AI-powered cinematic photo enhancement web platform, facilitating the transformation of user-uploaded images into visually captivating cinematic masterpieces. At its core, the architecture comprises a hierarchical structure of interconnected components, each designed to perform specific image enhancement tasks with precision and efficiency. The architecture begins with an initial preprocessing stage, where raw input images undergo essential transformations to standardize their format and prepare them for subsequent processing.

This preprocessing step includes operations such as resizing, normalization, and noise reduction, ensuring uniformity and enhancing the quality of input data. Following preprocessing, the processed images enter a series of specialized modules, each tailored to address distinct aspects of image enhancement. These modules encompass a wide range of techniques, including color enhancement, contrast adjustment, edge detection, and texture preservation, among others. Each module leverages advanced machine learning algorithms and deep neural networks to analyze image content and apply appropriate enhancements while preserving crucial details and aesthetic qualities. This section lists some ideas for extending the tutorial that you may wish to explore.

• Your Own Images. Experiment with Pillow functions for reading and muscipulatin images with your own image data

• More Transforms Review the Pillow API documentation and experiment with adds- tional image manipulation functions

• Image Pre-processing Write a function to creste augmented versions of an image ready for use with a deep learning neural network**. [3**]

4.2. Style Transfer Model Adaptation

Style transfer model adaptation is a crucial component of our AI-powered cinematic photo enhancement web platform, enabling the transformation of user-uploaded photos into visually stunning cinematic masterpieces. This process involves fine-tuning pre-existing style transfer models to align with our project's objectives and aesthetic preferences. Initially, we select and evaluate several state-of-the-art style transfer models, considering factors such as performance, computational efficiency, and flexibility. Style transfer is a process of migrating a style from a “style image” to a “content image”.

The goal is to be able to generate different renditions of the same scene according to different style images. **[4].** Once a suitable model is identified, we proceed with adapting it to meet the specific requirements of our platform. Adaptation begins by adjusting the model's hyperparameters, including style weight, content weight, and learning rate, to achieve the desired balance between style fidelity and content preservation. We also explore techniques such as neural style transfer and perceptual loss functions to enhance the model's ability to capture intricate stylistic details while maintaining image coherence. Furthermore, we leverage transfer learning to expedite model adaptation by initializing the network weights with pre-trained parameters from models trained on large-scale image datasets. This approach enables us to capitalize on the knowledge learned by existing models and fine-tune them to specialize in cinematic style transfer

5. TESTING AND EVALUATION

Testing and evaluation involve unit testing for meticulous validation of AI model components, ensuring accurate image processing and style transfer. User testing procedures assess website usability, refining the user experience based on valuable feedback, while performance testing metrics measure responsiveness and efficiency. These phases collectively safeguard the excellence of cinematic photo enhancement, ensuring a seamless user experience and optimal website performance.

5.1. Unit Testing Protocols

Unit testing protocols play a pivotal role in ensuring the robustness and reliability of the AI-powered

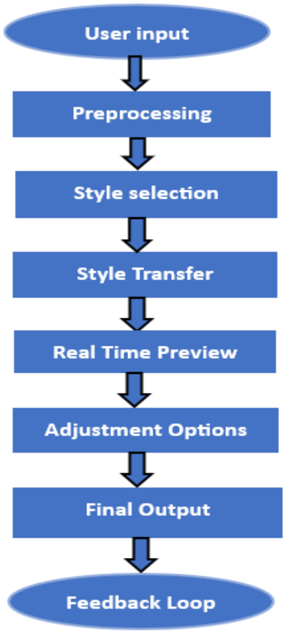

Fig 5.1. Photo Enhancement Process.

cinematic photo enhancement web platform. These protocols encompass a systematic approach to validate the functionality of individual components within the AI models, guaranteeing accurate image processing and effective style transfer. At the heart of unit testing is the decomposition of the software into smaller units, typically functions or methods, which are then subjected to rigorous testing in isolation. Fig.5.1. represent bridging the gap between development and final implementation. Unit testing rigorously examines individual components of the AI model to guarantee precise image processing and style transfer capabilities. For our platform, this involves testing each AI model component independently, including the image processing algorithms and style transfer mechanisms.

The resulting fully-convolutional net is then applied to the whole (uncropped) image. The result is a class score map with the number of channels equal to the number of classes, and a variable spatial resolution, dependent on the input image size. **[7]**. The testing process begins with the formulation of test cases that encompass a range of scenarios and edge cases, covering various input data types, parameter configurations, and boundary conditions. These test cases are meticulously designed to assess the model's behavior under different circumstances and to uncover any potential bugs or inconsistencies. Once the test cases are defined, they are executed systematically using automated testing frameworks, such as Py Test or TensorFlow's built-in testing utilities. The results of each test case are then analyzed to verify whether the model behaves as expected and meets the specified requirements. Throughout the testing phase, thorough documentation is maintained to track the test cases, their outcomes, and any issues encountered. This documentation serves as a valuable resource for debugging and troubleshooting, facilitating the identification and resolution of defects in the AI models.

5.2. User Testing Procedures

User testing procedures are integral to assessing the usability, functionality, and overall user experience of the AI-powered cinematic photo enhancement web platform. These procedures involve soliciting feedback from target users through structured testing sessions, surveys, and interviews to gain insights into their interaction with the platform. The user testing process begins with the recruitment of a diverse pool of participants who represent the platform's target audience. These participants are selected based on demographic factors, such as age, gender, and level of expertise in photo editing, to ensure a comprehensive evaluation of the platform's usability and appeal across different user segments.

During the testing sessions, participants are tasked with performing specific actions and scenarios within the platform, such as uploading a photo, applying cinematic effects, and adjusting enhancement parameters. Observers carefully monitor participants' interactions, noting any usability issues, confusion, or challenges encountered during the tasks. Following the testing sessions, participants are asked to provide feedback through surveys or interviews, where they can express their opinions, preferences, and suggestions for improvement. This feedback is analyzed to identify recurring themes, pain points, and areas of strength within the platform. The insights gleaned from user testing inform iterative refinements and enhancements to the platform's design, functionality, and user interface. By incorporating user feedback into the development process, the platform can evolve to better meet the needs and expectations of its target audience, ultimately resulting in a more engaging and user-friendly experience.

5.3. Performance Testing Metrics

Performance testing metrics play a crucial role in evaluating the responsiveness, efficiency, and scalability of the AI-powered cinematic photo enhancement web platform. These metrics provide quantitative measures of the platform's performance under various conditions, helping to identify bottlenecks, optimize resource utilization, and ensure a seamless user experience. When deeper networks are able to start converging, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly **[8]** Key performance testing metrics include response time, throughput, and resource utilization. Response time measures the time taken for the platform to respond to user requests, such as uploading a photo or applying a cinematic effect. Throughput represents the rate at which the platform can process multiple requests simultaneously, indicating its overall processing capacity and efficiency.

Resource utilization metrics track the usage of system resources, such as CPU, memory, and network bandwidth, during peak load conditions, helping to identify potential resource constraints and scalability issues. Other important performance metrics include error rates, concurrency levels, and scalability thresholds. Error rates quantify the frequency of errors or failures encountered during testing, highlighting areas for improvement in error handling and resilience. Concurrency levels assess the platform's ability to handle multiple concurrent users or requests without degradation in performance. Scalability thresholds determine the maximum workload or user load that the platform can sustain while maintaining acceptable performance levels, guiding decisions on infrastructure provisioning and capacity planning. By systematically measuring and analyzing these performance metrics, developers can identify performance bottlenecks, optimize system configurations, and ensure that the platform meets performance objectives and user expectations. Continuous monitoring and testing allow for ongoing performance optimization and refinement, ensuring that the platform delivers a reliable, responsive, and high-performance experience for users.

6. RESULTS AND DISCUSSIONS

Quantitative results analysis examines statistical data, providing insights into user satisfaction scores, processing times, and website performance. Qualitative findings discussion incorporates user feedback and observations, offering a nuanced understanding of the emotional resonance and user experience during testing phases.

Fig 6.1. Raw Data of the Theme

6.1. Quantitative Results Analysis

The culmination of user interactions and website usage manifests in the realm of quantitative results analysis. This meticulous examination involves delving into statistical data encompassing user satisfaction scores, processing times, and overall website performance. By quantifying the user experience, we gain valuable insights into the efficiency of our AI models and the seamless nature of the cinematic photo enhancement process. Statistical data becomes the compass guiding further refinements, ensuring that the quantitative lens captures the essence of user satisfaction and operational excellence.

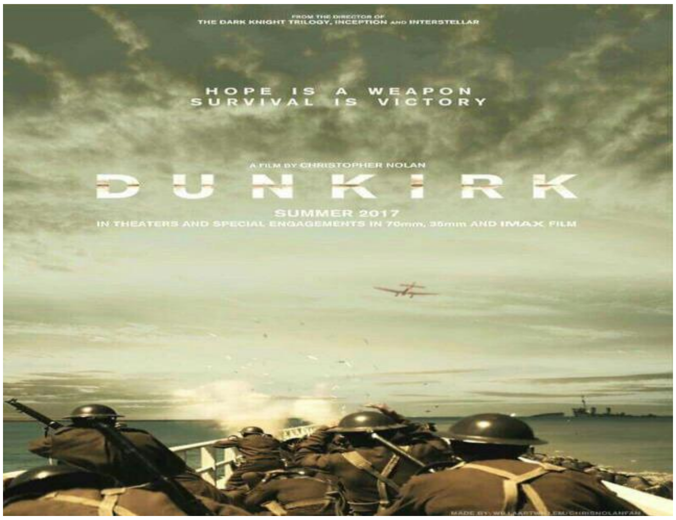

Fig 6.2. Theme of the Movie(Dunkirk)

6.2. Qualitative Findings Discussion

Beyond the numbers lies the rich tapestry of qualitative findings discussion. This segment embraces user feedback and observations gathered during testing phases, offering a nuanced understanding of the user experience. Qualitative insights delve into the intricacies of user interactions, perceptions of cinematic enhancements, and the emotional resonance created through the fusion of technology and creativity. It is within this qualitative realm that the true impact of cinematic photo enhancement is unraveled, providing a narrative that transcends statistics and encapsulates the essence of user delight and engagement.

Fig 6.3. Result of the Movie Theme

7. CONCLUSION

The AI-powered cinematic photo enhancement web platform represents a significant advancement in web development, leveraging AI technologies to deliver immersive and visually captivating user experiences. Through meticulous methodology, including tool selection, model development, and testing procedures, the platform achieves its objectives of seamlessly integrating AI models, enhancing user interaction, and delivering cinematic photo effects in real-time. The project's contributions extend to user experience design, performance optimization, and practical implications for AI-driven web applications. Moving forward, ongoing research and development efforts will continue to enhance the platform's capabilities, addressing emerging challenges and opportunities in AI-driven web development. Overall, the project underscores the transformative potential of AI in shaping the future of web experiences, offering innovative solutions for engaging and impactful user interactions.

REFERENCES

[1] Geron, A. (2019). Hands-On Machine Learning with Scikit-Learn, Kera's, and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems (2nd ed.). O'Reilly Media.

[2] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[3] Brownlee, J. (2020). Deep Learning for Computer Vision. Machine Learning Mastery.

[4] Gay's, L. A., Ecker, A. S., & Bethge, M. (2016). Image Style Transfer Using Convolutional Neural Networks. IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[5] Johnson, J., Alai, A., & Fei-Fei, L. (2016). Perceptual Losses for Real-Time Style Transfer and Super-Resolution. European Conference on Computer Vision (ECCV).

[6] Huang, J. B., Singh, A., Ahuja, N., & Learned-Miller, E. (2017). Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. International Conference on Learning Representations (ICLR).

[7] Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. sIEEE Transactions on Pattern Analysis and Machine Intelligence.

[8] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. IEEE Conference on Computer Vision and Pattern Recognition.

[9] Zhang, L., Zhang, L., & Mou, X. (2019). Neural Style Transfer: A Review. IEEE Transactions on Visualization and Computer Graphics.

[10] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Instelligence