**Integrating Pioneer Viewing Platforms with Learning-Based 360° Video Super-Resolution: A Comprehensive Approach for Enhancing Immersion and Evaluating Perceptual Capacity**

***Final Report***

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**ABSTRACT**

Omnidirectional videos have become integral to Virtual Reality (VR) experiences, providing users with interactive and captivating visual narratives. The introduction of 360° Viewing Platforms has significantly transformed the landscape of immersive content consumption, particularly in the realm of 360° videos. However, the challenge lies in aligning the technical improvements of 360-degree videos with the quality of experience and services for viewers. While much attention is given to technical aspects, such as PSNR evaluation, the immersive nature of 360-degree content often gets overlooked. Insufficient research on viewer perception and the absence of standardized measurement methods creates further hurdles. It's crucial to consider not only the technical enhancements but also how these improvements contribute to a more immersive and engaging experience for viewers. Additionally, ensuring seamless performance across different devices is essential for widespread adoption and utility of these technologies.

In this research work, we aim to introduce innovative ways to enhance the video-watching experience by seamlessly integrating how we watch and improving clarity and smoothness. Our focus extends beyond technical aspects, prioritizing the viewer's emotional satisfaction, particularly in immersive 360-degree videos. We are conducting research to establish standardized measures for this emotional experience. Additionally, our goal is to ensure that these techniques are scalable and user-friendly, facilitating widespread adoption and usefulness for a broad audience.

Keywords*—* *Pioneer Viewing Platform, 360° Video, Immersive Experience, Virtual Reality (VR), Human Perception, Quality of Experience, Quality of Services*

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Table 1: Comparisons between Literature papers

**LIST OF ACRONYMS AND ABBREVIATIONS**

1. VR - Virtual Reality
2. PSNR - Peak Signal-to-Noise Ratio
3. SSIM - Structural Similarity Index
4. 360VDS - 360° Video Dataset
5. S3PO - Spherical Signal Super-resolution with Proportioned Optimization
6. ODV - Omnidirectional Videos
7. VSR - video super-resolution
8. 360VSR - 360° Video Super-Resolution
9. FoV - Field-of-View
10. SR - Super-Resolution
11. DRL - Deep Reinforcement Learning
12. QoE - Quality of Experience
13. DNN - Deep Neural Network
14. CNN - Convolutional Neural Network
15. MEC - Multi Access Edge Computing
16. HPC - High-Performance Computing
17. R2D2 - Replenished Recurrency with Dual-Duct
18. GAN - Generative Adversarial Network
19. SSR - Spherical Super-Resolution
20. ERP - Equirectangular Projection
21. OISR - Omnidirectional Image Super-Resolution
22. GCP - Google Cloud Platform
23. CDN - Content Delivery Network
24. NFRs - Non-Functional Requirements
25. RABC - role-based access control
26. ROI - Return on Investment
27. NICs - Network Interface Cards
28. DBMS - Database Management System
29. IDEs - Integrated Development Environments
30. API - Application programming interface
31. **Introduction**

**1.1 Introduction of the project Domain**

360-degree video technology has ushered in a new era of immersive and interactive visual experiences, fundamentally altering how we perceive and engage with digital content. Unlike traditional videos that offer a fixed perspective determined by the camera angle, 360-degree videos provide viewers with the ability to explore scenes from multiple viewpoints, creating a sense of presence and involvement as if they were physically present in the environment being depicted [11]. This revolutionary shift in video content delivery has opened a myriad of possibilities across various industries, including entertainment, education, tourism, real estate, and training.

One of the fundamental differences between conventional videos and 360-degree videos lies in the way content is captured and presented. Traditional videos are captured using a fixed camera angle, limiting the viewer's perspective to what is framed within the camera's field of view. In contrast, 360-degree videos are captured using specialized cameras equipped with multiple lenses that capture a full 360-degree view of the surroundings. This immersive capture technique allows viewers to freely navigate the video's environment, panning, tilting, and zooming to explore different perspectives and points of interest.

Despite the immense potential and excitement surrounding 360-degree video technology, several challenges and research gaps persist, hindering its widespread adoption and optimal utilization. One of the primary challenges is the limited understanding of viewer perception and the subjective nature of evaluating the quality of experience in immersive content. Unlike traditional video quality metrics such as resolution, frame rate, and bit rate [3] , which can be objectively measured, assessing the immersive experience in 360-degree videos requires a deeper understanding of human perception, attentional focus, and emotional engagement.

Another challenge is the lack of standardized measurement methods and evaluation frameworks specifically tailored for assessing the quality of experience in 360-degree videos. Existing metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) used in traditional video quality assessment [1] may not capture the unique aspects of immersive content, such as spatial presence, interactivity, and user engagement. This gap in research and evaluation methodologies poses a significant obstacle to optimizing 360-degree video content for maximum viewer satisfaction and impact.

In our project, we recognize the critical importance of addressing these challenges and research gaps to unlock the full potential of 360-degree video technology. Our focus is on enhancing the quality of experience in 360-degree videos by leveraging cutting-edge advancements in video processing, interactive storytelling, and user-centric design principles. By integrating innovative techniques such as spatial audio, dynamic scene rendering, and user-driven narratives, we aim to create captivating and immersive experiences that resonate with viewers on a deeper level.

Our approach emphasizes a holistic understanding of user perception, emotional response, and engagement metrics to evaluate and enhance the immersive experience in 360-degree videos. Through user studies, qualitative assessments, and iterative design refinements, we strive to create compelling content that not only captivates audiences but also leaves a lasting impression, driving the evolution of immersive storytelling and digital media consumption.

In conclusion, the focus on enhancing the quality of experience in 360-degree videos represents a pivotal trend in the realm of digital content creation and consumption. By addressing the challenges and research gaps associated with immersive content, we aim to unlock new possibilities for storytelling, education, entertainment, and beyond, shaping the future of visual communication and human-computer interaction in the digital age.

**1.2 Aim of the project**

The aim of the project is to develop and implement integrated solutions that effectively combine viewing platforms and 360° video super-resolution techniques, leveraging the potential synergies between these technologies. The primary focus will be on enhancing perceptual quality and user experience in immersive environments, with special attention given to formats like 360-degree video/frames beyond mere technical improvements. The project aims to conduct comprehensive research to establish standardized evaluation metrics that accurately assess the perceptual capacity of users within integrated environments. Additionally, the project aims to develop scalable techniques that efficiently merge viewing platform capabilities with super-resolution algorithms, enabling effective handling of larger tasks and promoting widespread adoption and usability of these integrated technologies.

**1.3 Objective of the project**

* Developing and implementing integrated solutions that seamlessly combine viewing platforms and 360° video super-resolution techniques, maximizing the potential synergies between these technologies.
* Focusing on enhancing perceptual quality and user experience in immersive environments, with a particular emphasis on formats like 360-degree video/frames going beyond just making them technically sharper or smoother.
* Conducting comprehensive research to establish standardized evaluation metrics for assessing the perceptual capacity of users within integrated environments
* Developing scalable techniques that efficiently merge viewing platform capabilities with super-resolution algorithms. The objective is to ensure that these integrated technologies can handle larger tasks effectively, promoting widespread adoption and usability.

**1.4 Scope of the project**

The scope of the project includes:

* Development of Integrated Solutions: The project will involve the development and implementation of integrated solutions that combine viewing platforms and 360° video super-resolution techniques. This includes designing and integrating software components to seamlessly merge these technologies and maximize their synergistic potential.
* Perceptual Quality and User Experience Enhancement: The project will focus on enhancing the perceptual quality and user experience in immersive environments, specifically targeting formats like 360-degree video/frames. The scope goes beyond technical improvements, aiming to create a more immersive and engaging experience for users by considering factors beyond just sharpness or smoothness.
* Research on Evaluation Metrics: Comprehensive research will be conducted to establish standardized evaluation metrics for assessing the perceptual capacity of users within integrated environments. The scope involves studying existing evaluation methods, identifying gaps, and developing or adapting metrics that effectively measure user perception and experience.
* Development of Scalable Techniques: The project will develop scalable techniques that efficiently merge viewing platform capabilities with super-resolution algorithms. The goal is to ensure that the integrated technologies can handle larger tasks effectively, promoting widespread adoption and usability. The scope includes researching and implementing efficient algorithms and approaches that can accommodate the demands of larger-scale applications.

**1.5 Targeted Audience**

The 360 Degree Video Platform targets a diverse range of users, including video enthusiasts, developers, researchers, and general users. Video enthusiasts, who have a keen interest in the latest video technologies, appreciate the platform’s ability to compare original and enhanced videos side by side and are highly engaged in providing detailed feedback. Developers use the platform to test and validate their video enhancement algorithms, improve user interfaces, and optimize streaming performance based on user feedback. Researchers collect user feedback data for studies on video quality assessment, streaming technologies, and user experience, leveraging the platform for algorithm evaluation and user perception analysis. General users, who enjoy watching high-quality 360-degree videos, benefit from the platform’s user-friendly design, allowing them to easily navigate, watch, and provide feedback on videos, thereby contributing to the overall data pool and enhancing the viewing experience for all. Together, these diverse user groups provide comprehensive insights that drive the continuous improvement of 360-degree video quality and user satisfaction.

1. **Literature survey**

The topic of the project represents a cutting-edge area in the field of immersive content delivery. The following literature survey table provides an overview of the existing research and related work in the domains of 360 video super-resolution developments. Along with the models and approach utilized in the study to build 360-degree video super-resolution, it also provides the contributions that are done by authors.

**2.1 Survey on Existing System**

In the papers [1], the author highlighted a key challenge – the limited spatial resolution in 360° videos and 360° video datasets to study. This constraint hinders the detailed representation of each viewing degree, compromising the overall visual quality in immersive experiences. The paper addresses this issue by introducing a novel 360° Video Dataset (360VDS) and proposing a new deep learning model, Spherical Signal Super-resolution with Proportioned Optimization (S3PO) which results was outstanding, for 360° Video Super-Resolution (360° VSR).

Looking at the paper of [2], they tackled the problem of current mobile networks struggling to provide high-quality Omnidirectional Videos (ODV). Noticing the potential in mobile GPUs for ODV processing that has not been fully utilized, they propose leveraging video super-resolution (VSR) to enhance ODV quality. However, the dynamic GPU capabilities and variability in mobile devices pose a challenge for VSR-enhanced ODV streaming. Their solution is OmniLive, an on-device VSR system tailored for mobile ODV live streaming. OmniLive handles GPU dynamics through an anytime inference-based VSR technique called Omni SR, featuring a neural network model with multiple exits and a dynamic inference scheduler.

The authors in the paper [3], they addressed the problem of low video resolution in mainstream panoramic cameras, which hampers a viewing experience similar to conventional displays. Additionally, network bandwidth limits high-resolution 360-degree video streaming. While existing methods address these challenges with viewport prediction and regional super-resolution, they fall short due to prediction errors and server-side pre-process consumption. Introducing RA360SR, a real-time acceleration-adaptive 360-degree video super-resolution system, the paper uses a dual-camera setup with Unity3D post-processing. To ensure a stable frame rate, they propose an acceleration-adaptive approach, dynamically switching super-resolution processing based on users' head movement acceleration.

Examining [4], they highlight the challenge of limited network bandwidth in 360-degree video streaming. While the common approach focuses on streaming high-quality video tiles within the user's Field-of-View (FoV), accurate FoV prediction is tough due to diverse user behaviors and changing network conditions. This paper introduces SR360, a framework using super-resolution (SR) techniques to trade off reduced network bandwidth by utilizing user devices' computation resources. Applying deep reinforcement learning (DRL), SR360 jointly decides on user FoV prediction, bitrate allocation, and SR enhancement, boosting low-resolution video tiles to high resolution at the client side.

The author [5], addressed the challenge of ultrahigh bandwidth and low latency in 360-degree video streaming, which impacts user quality of experience (QoE). Current methods combining field of view (FoV) prediction and adaptive video streaming have limitations. To overcome these, the paper introduces VRFormer, a DRL-based 360-degree video streaming method with FoV prediction and super resolution (SR). Using a content-aware transformer network, it predicts long-term FoV by considering user head movement, eye-tracking, and attention. Additionally, a DNN-based SR network on VR devices reconstructs high-definition video content. The approach adapts rates for future tiles and dynamically controls video content reconstruction using a DRL-based network.

The paper [6], author tackled the challenge of high bandwidth requirements in 360° videos. Current systems use viewport prediction, but it often results in errors, impacting user experience. Introducing PARSEC, a 360° video streaming system, the paper reduces bandwidth while enhancing video quality. PARSEC balances bandwidth with client-side computation, employing a super-resolution approach. The server compresses the video, and the client uses a deep learning model to significantly improve its quality. PARSEC addresses challenges related to super-resolution in 360° video streaming, including large models, slow inference rates, and variability in enhanced video quality.

Looking at the paper of [7], they highlighted the issue of high bandwidth demands in mobile networks for popular 360° videos with larger spherical frames. In this initial work, the proposal combines frame interpolation and super-resolution to optimize tile-based 360° video delivery. By streaming at low qualities in the network and increasing quality with Multi-Access Edge Computing, a mechanism is introduced for adaptive quality conversion at the client side. This approach improves average video quality by 30% and achieves a bandwidth saving of 43.3% compared to existing tile-based streaming.

The authors in the paper [8], they addressed the issue of inefficiency in handling spherical signals, leading to pixel waste and distortion. Recent advances in spherical CNNs address this but face challenges in real-world applications due to extensive bandwidth requirements. To address bandwidth waste in 360-degree video streaming and enhance efficiency, the paper introduces Focused Icosahedral Mesh. This method represents small areas and constructs matrices to rotate spherical content, addressing both computational and bandwidth concerns. Additionally, a novel Vertex Shuffle operation improves performance compared to previous methods. Applied to a super-resolution model, this is the first to propose a spherical super-resolution model directly operating on a mesh representation of spherical pixels in 360-degree data.

Looking at the paper of [9], they highlighted the issue of traditional viewport-aware streaming methods being theoretically effective but unreliable in practice due to variable available bandwidth. Introducing Sophon, a buffer-based and neural-enhanced streaming framework, the paper utilizes a double buffer design, super-resolution technique, and viewport-aware strategy to enhance user experience. Additionally, it proposes visual saliency-aware prefetch and super-resolution model selection schemes to address challenges related to insufficient computing resources and dynamic user preferences. The paper introduces corresponding metrics and develops a lightweight buffer occupancy-based prefetch algorithm and a deep reinforcement learning method, balancing bandwidth consumption, computing resource utilization, and content quality enhancement.

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| **Ref. No.** | **Title of Paper** | **Author and Publiction** | **Contribution** | **Model Used / Approach** |
| [1] | Omnidirectional Video Super-Resolution Using Deep Learning | Arbind Agrahari Baniya , Tsz-Kwan Lee , Peter W. Eklund , and Sunil Aryal  April 2023 | * Created a novel 360° Video Dataset (360VDS) having 590 videos to address the limited availability of 360° video datasets * Proposed a novel deep learning model called Spherical Signal Super-resolution with a Proportioned Optimization (S3PO) for 360° Video Super-Resolution (360° VSR) | * Designed a deep learning model called Spherical Signal Super-resolution with a Proportioned Optimization (S3PO) for 360° Video Super-Resolution (360° VSR). |
| [2] | OmniLive: Super-Resolution Enhanced 360° Video Live Streaming for Mobile Devices | Seonghoon Park, Yeonwoo Cho, Hyungchol Jun, Jeho Lee, Hojung Cha  Jun 2023 | * Proposed OmniLive, an on-device VSR system for mobile ODV live streaming which Addressed the dynamicity of GPU capability with an anytime inference-based VSR technique called Omni SR. | * Designed a VSR deep neural network (DNN) model with multiple exits and an inference scheduler that decides on the exit of the model at runtime. |
| [3] | RA360SR: A Real-time Acceleration-adaptive 360-degree Video Super-resolution System | Jiapeng Chi, Dirk Reiners, Carolina Cruz-Neira  Oct 2022 | * Developed a real-time acceleration-adaptive 360-degree video super-resolution system called RA360SR to improve the video resolution provided by existing panoramic video cameras and address the network bandwidth bottleneck for high-resolution 360-degree video streaming. | * Designed real-time acceleration-adaptive approach for 360-degree video super-resolution to implement the real-time super-resolution model processing. And acceleration-adaptive approach to ensure a more stable frame rate. |
| [4] | SR360: boosting 360-degree video streaming with super-resolution | Jiawen Chen, Miao Hu, Zhenxiao Luo, Zelong Wang, Di Wu  Jun 2020 | * Proposed a new framework called SR360 that utilizes super-resolution (SR) techniques to enhance the streaming of 360-degree videos by reducing network bandwidth while maintaining high video quality. | * Deep reinforcement learning (DRL) is adopted for the SR360 framework to make a set of decisions jointly, including user FoV prediction, bitrate allocation, and SR enhancement |
| [5] | VRFormer: 360-Degree Video Streaming with FoV Combined Prediction and Super resolution | Zhihao Zhang, Haipeng Du, Shouqin Huang, Weizhan Zhang, Qinghua Zheng  Dec 2022 | * Proposed a deep reinforcement learning (DRL)-based 360-degree video streaming method named VRFormer with FoV combined prediction and super resolution (SR) to improve the quality of experience (QoE) for users in 360-degree video streaming . | * DRL-based 360-degree video streaming method to improve the quality of experience and A DNN-based SR network to reconstruct high-definition video content on VR devices, enhancing the visual quality of the streamed videos |
| [6] | Streaming 360-Degree Videos Using Super-Resolution | Mallesham Dasari, Arani Bhattacharya, Santiago Vargas, Pranjal Sahu, Aruna Balasubramanian, Samir R. Das  Jul 2020 | * Created a 360° video streaming system called PARSEC that reduces bandwidth requirements while improving video quality. | * PARSEC uses super-resolution techniques, where the video is compressed at the server and enhanced to a higher quality using a deep learning model on the client side. |
| [7] | Edge assisted frame interpolation and super resolution for efficient 360-degree video delivery | Chamara Madarasingha, Kanchana Thilakarathna  Oct 2022 | * Proposed a method that combines frame interpolation and super resolution techniques to optimize the delivery of 360° videos. | * Frame interpolation and super resolution methods, that involves streaming the videos at low qualities in the network and then leveraging Multi Access Edge Computing (MEC) to increase the video quality. |
| [8] | Applying VertexShuffle Toward 360-Degree Video Super-Resolution on Focused-Icosahedral-Mesh. | Na Li, Yao Liu  Jun 2021 | * Introduced the use of Focused Icosahedral Mesh to represent a small area and construct matrices to rotate spherical content, addressing the bandwidth waste problem associated with 360-degree video streaming and saving computation . | * Designed a novel VertexShuffle operation that significantly improves both the performance and efficiency compared to the original MeshConv Transpose operation, leading to better results in terms of super-resolution on 360-degree inputs . |
| [9] | Sophon: Super-Resolution Enhanced 360° Video Streaming with Visual Saliency-aware Prefetch | Jianxin Shi, Li Pu, Xinjing Yuan, Qianyun Gong, Jingdong Xu  Oct 2022 | * Presented Sophon, a buffer-based and neural-enhanced streaming framework that combines the double buffer design, super-resolution technique, and viewport-aware strategy to improve user experience in 360° video streaming. | * Developed a lightweight buffer occupancy-based prefetch algorithm and a deep reinforcement learning method to optimize bandwidth consumption, computing resource utilization, and content quality enhancement. |
| [10] | Online Video Super-Resolution using Information Replenishing Unidirectional Recurrent Model | Arbind Agrahari Baniya, Tsz-Kwan Lee, Peter W. Eklund, Sunil Aryal, Antonio Robles-Kelly May 2023, | Proposed a novel unidirectional recurrent model for Video Super-Resolution (VSR) called "Replenished Recurrency with Dual-Duct" (R2D2) that can be used in an online application setting | unidirectional recurrent model for Video Super-Resolution (VSR) called "Replenished Recurrency with Dual-Duct" (R2D2). |
| [11] | A Single Frame and Multi-Frame Joint Network for 360-degree Panorama Video Super-Resolution | Hongying Liu,Zhubo Ruan,Chaowei Fang, Peng Zhao, Fanhua Shang,Yuanyuan Liu, Lijun Wang Aug 2020 | Proposed a novel single frame and multi-frame joint network (SMFN) for recovering high-resolution spherical videos from low-resolution inputs | Designed a a novel single frame and multi-frame joint network (SMFN) for recovering high-resolution spherical videos from low-resolution inputs |
| [12] | 360-Degree Image Super-Resolution Based on Single Image Sample and Progressive Residual Generative Adversarial Network | Liuyihui Qian, Xiaojun Liu, Juan Wu, Xiaoqing Xu, Han Zeng Jul 2022 | Purpose a method for super-resolution of 360-degree images using a single image sample and a generative adversarial network (GAN) | utilizes a generative adversarial network (GAN) model called Progressive Residual GAN (PRGAN) for training a super-resolution model on a single 360-degree image sample. |
| [13] | DRL360: 360-degree Video Streaming with Deep Reinforcement Learning | Yuanxing Zhang, Pengyu Zhao, Kaigui Bian, Yunxin Liu, Lingyang Song, Xiaoming Li April 2019 | Presented a Deep Reinforcement Learning (DRL) based framework called DRL360 for 360-degree video streaming, which optimizes multiple Quality of Experience (QoE) objectives across dynamic features. | a Deep Reinforcement Learning (DRL) based framework called DRL360 |
| [14] | Applying VertexShuffle toward 360-degree video super-resolution | Na Li, Yao Liu Jun 2021 | Designed a novel spherical super-resolution (SSR) approach for 360-degree videos, inspired by recent state-of-the-art 2D super-resolution models and spherical CNNs. | proposed the Focused Icosahedral Mesh to represent a small area on the sphere and construct matrices to rotate spherical content to the focused mesh area. |
| [15] | 360 super-resolution method for multi-view 360-degree image and image processing apparatus | Kang Je Won, Kim Hee Jae, Lee Byung Uk Aug 2020 | proposed a method for performing super-resolution for multi-view 360-degree images, which involves converting a low-resolution target image and estimating flow based on a high-resolution reference image and the up-sampled target image | presents a novel approach for super-resolution of multi-view 360-degree images using neural network models and feature maps, |
| [16] | Scalable Omnidirectional Video Coding for Real-Time Virtual Reality Applications | Deyang Liu, Ping An, Ran Ma, Wenfa Zhan, Liefu Ai Oct 2018 | Proposed of a scalable omnidirectional video coding method that improves coding efficiency and provides three-layer scalability. | Introduced of a down-sampling procedure of equirectangular projection (ERP) video with a corresponding super-resolution method to save bandwidth and provide spatial resolution scalability. |
| [17] | Omnidirectional Image Super-resolution via Latitude Adaptive Network | Xin Deng, Hao Wang, Mai Xu, Li Li, Zulin Wang Jan 2022 | Proposed a novel latitude-aware upscaling network, LAU-Net+, for omnidirectional image super-resolution (ODI-SR) that considers the nonuniformly distributed pixel density and geometric distortion across latitudes in ODIs. | model for omnidirectional image super-resolution (ODI-SR) is called LAU-Net+ |
| [18] | TCCL-Net: Transformer-Convolution Collaborative Learning Network for Omnidirectional Image Super-Resolution | Feng Shao May 2023 | proposed a novel end-to-end network called TCCL-Net for Omnidirectional Image Super-Resolution (OISR) which utilizes Swin Transformer blocks and residual convolution blocks to extract long-range and short-range dependencies, enabling the extraction of rich and heterogeneous features from both branches. | novel end-to-end network called TCCL-Net for Omnidirectional Image Super-Resolution (OISR) |

*Table 1: Comparisons between Literature papers*

* 1. **Gap Identified**

The literature survey reveals significant gaps in existing research on 360 video platforms, specifically regarding transparency, interpretability, and feature selection methods. These key gaps include:

* Lack of Integrated Solutions: Current viewing platforms and 360° video super-resolution techniques often operate in isolation, not taking full advantage of potential synergies.
* Perceptual Focus: Most existing solutions focus on technical aspects like resolution and framerate, but less on perceptual quality and user experience in an immersive environment. Especially for immersive video formats like 360-degree video/frames.
* Evaluation Metrics: Insufficient research has been conducted to evaluate the perceptual capacity of users within these integrated environments.
* Scalability: Current techniques might not scale efficiently when merging viewing platform capabilities with super-resolution algorithms.

**2.3 Problem Statement**

* Current viewing platforms and 360° video super-resolution techniques operate in isolation. There is a failure to exploit potential synergies that could enhance overall performance.
* Current research primarily focused on technical aspects such as resolution and frame rate, neglecting the importance of perceptual quality and user experience in immersive environments, particularly for formats like 360-degree video/frames.
* Insufficient research has been conducted to establish evaluation metrics for the perceptual capacity of users within integrated environments. The absence of standardized metrics hinders the comprehensive assessment of user experience in such contexts.
* Current techniques may not efficiently scale when integrating viewing platform capabilities with super-resolution algorithms. Scalability issues pose a challenge in achieving seamless integration, potentially limiting the broader adoption and effectiveness of these technologies.

1. **Requirement Analysis**

**3.1 Requirements**

**3.1.1 Functional**

1. **Developing and Implementing Integrated Solutions**

* Viewing Platform Integration:
  + Developing a 360° video player that supports a variety of video formats and resolutions.
  + Implementing features for uploading and streaming 360° videos.
  + Ensuring the platform is compatible with different devices (VR headsets, mobile devices, desktops).
* Synergy Maximization:
  + Optimizing the integration to minimize latency and processing time.
  + Allowing users to compare original and enhanced videos within the platform.

1. **Enhancing Perceptual Quality and User Experience**

* User Experience Design:
  + Designing an intuitive and user-friendly interface for the video player.
  + Including features for easy navigation within 360° videos (e.g., drag-and-view, zoom).
  + Providing interactive elements such as hotspots, annotations, and information overlays.
* Perceptual Quality Enhancement:
  + Implementing adaptive streaming to adjust video quality based on user’s bandwidth and device capabilities.
  + Providing customization options for users to adjust viewing settings according to their preferences.

1. **Establishing Standardized Evaluation Metrics**

* Research and Development:
  + Conducting user studies to gather data on perceptual quality in immersive environments.
  + Developing metrics for assessing perceptual capacity, including visual clarity, comfort, and immersion.
  + Creating standardized tests and surveys to collect consistent user feedback.
* Evaluation Framework:
  + Implementing a feedback collection system integrated into the viewing platform.
  + Developing dashboards and reporting tools to visualize user study results and metric analyses.

1. **Developing Scalable Techniques**

* Scalability of Viewing Platform:
  + Using cloud infrastructure (e.g., Google Cloud Platform) to ensure the platform can scale to handle large numbers of users and videos.
  + Implementing load balancing and auto-scaling features to manage traffic spikes and ensure smooth performance.
  + Implementing a scalable storage solution for storing large volumes of 360° video data.
* Promoting Widespread Adoption:
  + Implementing secure user authentication and authorization mechanisms.
  + Providing different access levels and permissions for users, content creators, and administrators.
* Content Delivery:
  + Using a Content Delivery Network (CDN) to ensure fast and reliable video streaming worldwide.
  + Developing tools for real-time monitoring of platform performance and user activity.
  + Implementing analytics to track video views, user interactions, and feedback trends.

These functional requirements will help ensure that your project not only meets technical goals but also provides a high-quality user experience and lays the foundation for future scalability and adoption.

**3.1.2 Non-Functional**

The non-functional requirements (NFRs) for your project will ensure the platform operates effectively and meets user expectations in terms of performance, reliability, and other quality attributes. Here are the detailed non-functional requirements:

1. **Performance:**

* The platform should load video content within 3 seconds.
* Video playback should start within 2 seconds after the user initiates play.
* The system should support active users simultaneously.

1. **Scalability**

* The platform should automatically scale up or down based on the current load, using cloud infrastructure.
* The system should handle an increase in user traffic without affecting performance.
* Ensuring efficient use of computing resources (CPU, GPU, memory) to optimize cost and performance.

1. **Reliability**

* The platform should be available all the time.
* Providing comprehensive error handling to gracefully manage failed video uploads and streaming issues.
* Logging all errors and providing meaningful error messages to users and administrators.

1. **Security**

* Ensuring all data (user data, video content) is encrypted.
* Implementing access control mechanisms to protect sensitive data and resources.
* Using secure authentication methods for user login.
* Implementing role-based access control (RBAC) to manage user permissions.

1. **Usability**

* Designing a user-friendly interface with intuitive navigation and clear instructions.
* Providing comprehensive documentation and help resources for users and developers.

1. **Maintainability**

* Designing the system with modular components to facilitate easy updates and maintenance.
* Ensuring that each module can be independently updated without affecting the overall system.

1. **Compatibility**

* Ensuring the platform works seamlessly across different devices, including desktops, mobile devices, and VR headsets.
* Supporting major web browsers (Chrome, Firefox, Safari, Edge) and operating systems (Windows, macOS, Android, iOS).

1. **Compliance**

* Ensuring the platform complies with relevant regulations and standards for data protection.
* Implementing features to support compliance, such as data deletion and user consent management.

1. **Monitoring and Logging**

* Implementing real-time monitoring of system performance, user activity, and resource utilization.
* Providing dashboards and alerts to notify administrators of potential issues.
* Implementing comprehensive logging for all system activities, including user interactions, processing tasks, and errors.

These non-functional requirements will help ensure that your platform is robust, secure, and capable of delivering a high-quality user experience under various conditions.

**3.3 System Specification:**

**3.3.1 Hardware Specification**

The hardware specifications for a 360° video platform with super-resolution capabilities need to support video processing, storage, and delivery efficiently. Here's a detailed outline of the necessary hardware:

1. **Server Hardware**

* CPU: Multi-core processors, preferably Intel Xeon or AMD EPYC with high clock speed for handling multiple video streams and processing tasks.
* GPU: High-performance GPUs such as NVIDIA Tesla, A100, or V100 for super-resolution processing using the S3PO model and other machine learning tasks.
* RAM: At least 16 GB, scalable up to 256 GB or more, to support high memory requirements for video processing and caching.
* Storage Type: SSDs for high-speed data access, along with HDDs for cost-effective bulk storage.
* Capacity: Start with at least 1 TB, scalable as needed based on video storage requirements.
* Bandwidth: High-speed network interfaces (10 Gbps or higher) to manage large data transfers efficiently.
* Network Interface Cards (NICs): Multiple NICs for redundancy and load balancing.

1. **Cloud Infrastructure (Google Cloud Platform)**

* Compute Engine Instances:
  + VMs: Custom VM types with high CPU, memory, and GPU specifications.
  + Preemptible VMs: For cost-effective processing of non-critical tasks.
* Cloud Storage:
  + Standard Storage: For general storage needs with moderate access frequency.
  + Nearline Storage: For infrequently accessed data.
* CDN Services: Utilize Google Cloud CDN for efficient content delivery, reduced latency, and improved user experience.

1. **Development and Testing Hardware**

* CPU: High-performance multi-core processors (Intel i7/i9 or AMD Ryzen 7/9).
* GPU: Dedicated GPUs (NVIDIA GeForce RTX series) for local testing of super-resolution models.
* RAM: At least 8 GB for handling multiple development environments and tools.
* Storage: SSDs with at least 1 TB capacity for fast read/write speeds.

1. **End-User Devices (For Testing)**

* VR Headsets: Examples- Oculus Rift, HTC Vive, or other high-quality VR headsets for testing the immersive experience.
* Mobile Devices: Platforms- Both iOS and Android devices with high-resolution displays.
* Desktop and Laptops: A range of devices with different specifications to ensure compatibility and performance across various hardware setups.
* Monitors: High-resolution monitors (4K or higher) for detailed video quality assessments.

**3.3.2 Software Specification**

The software specifications for a 360° video platform with super-resolution capabilities involve a range of technologies for video processing, storage, content delivery, user interaction, and management. Here's a detailed outline of the necessary software components:

1. **Backend Software**

* Python: For machine learning tasks, including super-resolution processing using the S3PO model.
* Frameworks and Libraries:
  + TensorFlow or PyTorch: Deep learning frameworks for implementing the super-resolution model.
  + OpenCV: Computer vision library for image and video processing tasks.
  + FFmpeg: Multimedia framework for handling video encoding, decoding, and streaming.
* Database Management System (DBMS): MySQL- Relational databases for structured data storage (e.g., user profiles, metadata).

1. **Frontend Software**

* Web Development:
  + PHP, CSS3, JavaScript: Frontend technologies for building responsive and interactive user interfaces.
* Bootstrap or Material-UI: UI frameworks for design consistency and responsiveness.
* Video Player: Use existing 360° video players or customize a player using libraries like Video.js or A-Frame for VR experiences.

1. **Cloud Services (Google Cloud Platform)**

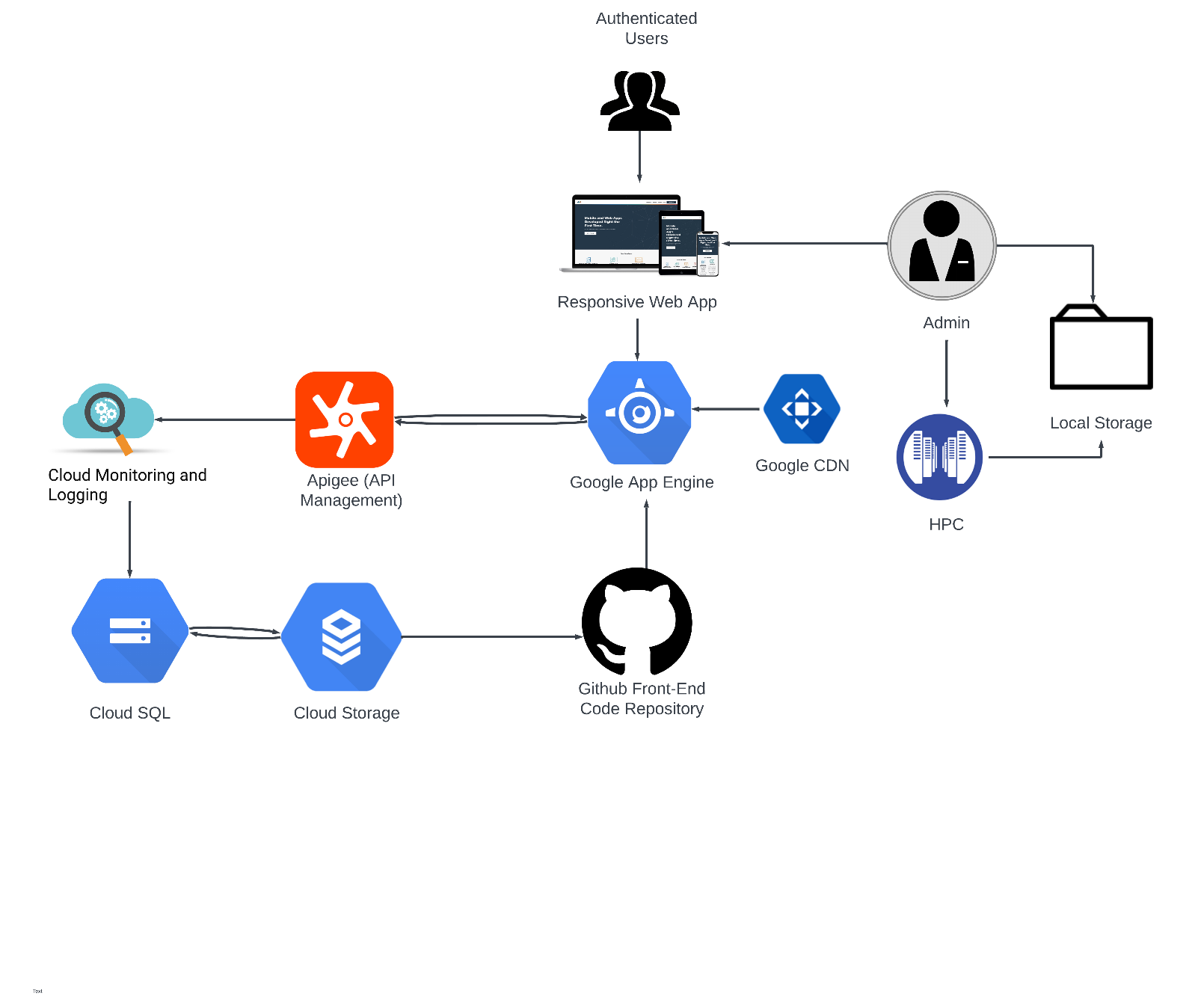
* Compute Engine: Deploy VM instances with custom configurations for backend processing, machine learning tasks, and API hosting.
* Utilize preemptible VMs for cost-effective batch processing and non-critical tasks.
* Cloud Storage: Store video files, user-generated content, and metadata in Google Cloud Storage buckets.
* Integrated Development Environments (IDEs): Use IDEs like Visual Studio Code, Atom, or PyCharm for backend and frontend development.
* Version Control: Git for version control and collaborative development.

1. **Analytics and Monitoring**

* Analytics Services: Integrate Google Analytics or similar services for tracking user engagement, video views, and performance metrics.
* Monitoring Tools: Use Google Cloud Monitoring or third-party tools for real-time monitoring of system health, resource utilization, and user activity.

1. **Project description**

**4.1 System Architecture**

****

*Figure 1: System Architecture of the video Platform*

The Above diagram represents a system architecture for a 360-degree video platform. Let's break down the components and explain their roles within this context:

1. Authenticated Users: These are users who can access and interact with the 360-degree video platform.
2. Responsive Web App: This is the primary interface for users, which adapts to different devices (desktops, tablets, smartphones). Users can view and interact with 360-degree videos through this application.
3. Admin: The admin is responsible for managing the platform, uploading and maintaining video content, and handling system configurations.
4. Local Storage: Used by the admin to store video files and other data locally before uploading them to the cloud.
5. HPC (High-Performance Computing): This component is used for intensive computational tasks such as video rendering, processing, and transcoding 360-degree videos to different formats and resolutions.
6. Google App Engine: A serverless platform where the web application is hosted. It manages the infrastructure, scaling, and deployment of the web app automatically.
7. Google CDN (Content Delivery Network): Delivers video content to users globally with high performance and low latency by caching the videos closer to users' locations.
8. GitHub Front-End Code Repository: Stores the source code of the web application. This includes HTML, CSS, JavaScript, and any other front-end assets. The code is pulled from this repository for deployment on the Google App Engine.
9. Apigee (API Management): Manages API requests from the web application to the backend services. It provides security, rate limiting, analytics, and other API management features.
10. Cloud SQL: A managed relational database service that stores user data, metadata about the videos (like titles, descriptions, tags), and other necessary application data.
11. Cloud Storage: Used to store the actual 360-degree video files. It provides scalable and durable storage for large video files.
12. Cloud Monitoring and Logging: Monitors the performance and health of the entire system. It logs activities, errors, and usage metrics to ensure smooth operation and helps in diagnosing issues.

**Data Flow and Interactions:**

1. User Interaction: Authenticated users access the platform through the responsive web app to view and interact with 360-degree videos.
2. Content Delivery: The video content is delivered via Google CDN, ensuring fast and reliable access to users around the world.
3. App Hosting and Code Deployment: The web app is hosted on Google App Engine, with its front-end code managed in the GitHub repository.
4. API Management: API requests from the web app (such as fetching video metadata, user authentication, etc.) are handled by Apigee, which routes them to the appropriate backend services.
5. Data Storage and Management: User data and video metadata are stored in Cloud SQL, while the actual video files are stored in Cloud Storage.
6. Monitoring: Cloud Monitoring and Logging continuously track system performance and log relevant activities for maintenance and troubleshooting.
7. Admin and HPC: Admins use HPC resources to process and transcode videos. The processed videos are then stored in Cloud Storage and made available through the web app.

By leveraging these cloud services, the platform ensures scalability, performance, and reliability, providing users with a seamless experience when accessing and interacting with 360-degree video content.

1. **Conclusion**

This paper will transform how people enjoy videos by seamlessly integrating viewing platforms with advanced 360° video enhancement methods. This approach is set to unlock the full potential of these technologies, delivering an immersive and top-quality viewing experience. Our focus will enhance how people perceive videos in immersive settings, especially in 360-degree formats. Beyond technical improvements, our goal is to ensure users have a genuinely enjoyable experience. This research will establish standard measurements for assessing user perception, providing a reliable method for the effectiveness of integrated environments. We anticipate creating adaptable methods that seamlessly merge viewing platform capabilities with advanced enhancement techniques, laying the foundation for these integrated technologies to efficiently handle even more significant tasks. Ultimately, to make these advancements widely accessible, allowing more people to benefit from and enjoy an enhanced future of immersive video experiences.

1. **Sample code**

**360-degree Video Enhanced code (Python)**

opt = parser.parse\_args()

opt.data\_dir = ''

systime = datetime.datetime.now().strftime('%Y-%m-%d-%H-%M')

def main():

    torch.manual\_seed(opt.seed)

    os.environ['CUDA\_VISIBLE\_DEVICES'] = opt.gpu\_devices

    if not torch.cuda.is\_available():

        raise Exception('No Gpu found, please run with gpu')

    else:

       use\_gpu = torch.cuda.is\_available()

    if use\_gpu:

        cudnn.benchmark = True

        torch.cuda.manual\_seed\_all(opt.seed)

    pin\_memory = True if use\_gpu else False

    print(opt)

    print('===> Loading Datasets')

    train\_set = get\_training\_set(opt.data\_dir, opt.scale, opt.data\_augmentation, opt.file\_list)

    train\_loader = DataLoader(dataset=train\_set, num\_workers=opt.threads, batch\_size=opt.batchsize, shuffle=True)

    print('===> DataLoading Finished')

    # Selecting network layer

    n\_c = 128

    n\_b = 10

    conv\_net = ResConvo(opt.scale, n\_c, n\_b) # initial filter generate network

    criterion = nn.SmoothL1Loss(reduction='none')

    p = sum(p.numel() for p in conv\_net.parameters())/1048576.0

    print('Model Size: {:.2f}M'.format(p))

    print(conv\_net)

    print('===> {}L model has been initialized'.format(n\_b))

    conv\_net = torch.nn.DataParallel(conv\_net)

    if use\_gpu:

        conv\_net = conv\_net.cuda()

        criterion = criterion.cuda()

    optimizer = optim.Adam(conv\_net.parameters(), lr = opt.lr, betas=(0.9, 0.999), eps=1e-8, weight\_decay=opt.weight\_decay)

    if opt.stepsize > 0:

        scheduler = lr\_scheduler.StepLR(optimizer, step\_size = opt.stepsize, gamma=opt.gamma)

    for epoch in range(opt.start\_epoch, opt.nEpochs+1):

        train(train\_loader, conv\_net, opt.scale, optimizer, epoch, use\_gpu, n\_c,criterion) #fed data into network

        scheduler.step()

        if (epoch) % (opt.snapshots) == 0:

            checkpoint(conv\_net, epoch)

def train(train\_loader, conv\_net, scale, optimizer, epoch, use\_gpu, n\_c,criterion):

    train\_mode = True

    epoch\_loss = 0

    conv\_net.train()

    total\_loss = 0

    for iteration, data in enumerate(train\_loader):

        x\_input, targets = data[0], data[1] # input and target are both tensor, input:[N,C,T,H,W] , target:[N,C,H,W]

        if use\_gpu:

            x\_input = Variable(x\_input).cuda()

            targets = Variable(targets).cuda()

        t0 = time.time()

        optimizer.zero\_grad()

        B, \_, T, \_ ,\_ = x\_input.shape

        out = []

        init = True

        for i in range(T-2):

            f1 = x\_input[:,:,i,:,:]

            f2 = x\_input[:,:,i+1,:,:]

            f3 = x\_input[:,:,i+2,:,:]

            if init:

                init\_temp = torch.zeros\_like(x\_input[:,0:1,0,:,:])

                init\_out = init\_temp.repeat(1, scale\*scale\*3,1,1)

                hid = init\_temp.repeat(1, n\_c, 1,1)

                hid, prediction = conv\_net(f1,f2,f3,hid,init\_out,init)

                out.append(prediction)

                init = False

            else:

                hid, prediction = conv\_net(f1,f2,f3,hid,prediction,init)

                out.append(prediction)

        predictions = torch.stack(out,dim=2)

        b,\_,n,\_,\_=targets.size()

        loss = criterion(predictions, targets)

        loss = torch.sum(wSmoothL1(predictions,loss))

        loss = loss/(b\*n)

        loss.backward()

        optimizer.step()

        epoch\_loss += loss.item()

        t1 = time.time()

        print("===> Epoch[{}]({}/{}): Loss: {:.4f} || Timer: {:.4f} sec.".format(epoch, iteration, len(train\_loader),loss.item(), (t1 - t0)),flush=True)

    print("Epoch-{} Avg Loss {}".format(epoch,(epoch\_loss/iteration)))

**360-degree video Platform Code (PHP, Laraval)**

<!DOCTYPE html>

<html lang="en">

<head>

    <meta charset="UTF-8">

    <meta http-equiv="X-UA-Compatible" content="IE=edge">

    <meta name="viewport" content="width=device-width, initial-scale=1.0">

    <link rel="stylesheet" href="{{ URL::asset('/home\_assets/style.css') }}">

    <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.3/dist/css/bootstrap.min.css" rel="stylesheet" integrity="sha384-QWTKZyjpPEjISv5WaRU9OFeRpok6YctnYmDr5pNlyT2bRjXh0JMhjY6hW+ALEwIH" crossorigin="anonymous">

    <link rel="stylesheet" href="https://cdn.jsdelivr.net/npm/sweetalert2@11/dist/sweetalert2.min.css">

    <link href="https://cdn.jsdelivr.net/gh/hung1001/font-awesome-pro-v6@44659d9/css/all.min.css" rel="stylesheet" type="text/css" />

    <title>Enhanced Vision 360</title>

</head>

<body>

    <nav class="flex-div">

        <div class="nav-left flex-div">

            <a href="{{route('home')}}"><img src="{{ URL::asset('home\_assets/images/logo3601.jpg') }}" class="logo" alt="" srcset=""></a>

        </div>

        <div class="nav-middle flex-div">

            <div class="search-box flex-div">

                <input type="text" id="searchInput" placeholder="Search.." onkeydown="handleSearchKey(event)">

                <img src="{{ URL::asset('home\_assets/images/search.png') }}" alt="" srcset="" onclick="filterVideosBySearch()">

            </div>

        </div>

        <div class="nav-right flex-div">

            <a href="{{route('uploadVideo')}}"><img src="{{ URL::asset('home\_assets/images/upload.png') }}" alt="" srcset=""></a>

            <a href="{{route('userVideos')}}"><img src="{{ URL::asset('home\_assets/images/more.png') }}" alt="" srcset=""></a>

            @if (!Auth::user())

                <a class="btn btn-success mx-2" href="{{route('register')}}">Register</a>

                <a class="btn btn-success mx-2" href="{{route('login')}}">Login</a>

            @else

               <div class="d-flex">

                    <div class="dropdown d-inline-block">

                        <button type="button" class="btn header-item waves-effect" id="page-header-user-dropdown" data-bs-toggle="dropdown" aria-haspopup="true" aria-expanded="false">

                            <img class="rounded-circle header-profile-user" src="{{ isset(Auth::user()->profile\_img) ? asset('profile\_photos/' . Auth::user()->profile\_img) : asset('/assets/images/users/avatar-9.png') }}" alt="Header Avatar">

                        </button>

                        <div class="dropdown-menu dropdown-menu-end" style="">

                            <a href="{{route('profile')}}" class="dropdown-item"><i class="bx bx-cog font-size-16 align-middle me-1"></i> <span key="t-my-wallet">Profile</span></a>

                            <a href="{{route('userVideos')}}" class="dropdown-item"><i class="bx bx-cog font-size-16 align-middle me-1"></i> <span key="t-my-wallet">Your Videos</span></a>

                            <a class=" logout-form dropdown-item text-danger" href="javascript:void();"><i class="bx bx-power-off font-size-16 align-middle me-1 text-danger"></i> <span key="t-logout">Logout</span></a>

                            <form action="{{ route('logout') }}" method="POST" style="display: none;">

                                @csrf

                            </form>

                        </div>

                    </div>

                </div>

            @endif

        </div>

    </nav>

<!-- Main Body -->

<div class="slider-container">

        <div class="slider-icon left" onclick="scrollCategoriesLeft()">

            <svg xmlns="http://www.w3.org/2000/svg" height="24" viewBox="0 0 24 24" width="24">

                <path d="M0 0h24v24H0V0z" fill="none"/>

                <path d="M15.41 7.41L14 6l-6 6 6 6 1.41-1.41L10.83 12z"/>

            </svg>

        </div>

        <div class="category-slider" id="categorySlider">

            <div class="category selected" id="all\_category" onclick="filterVideos(0)">All</div>

            @foreach ($categories as $category)

                <div class="category" id="category-{{ $category->id }}" onclick="filterVideos({{ $category->id }})">{{ $category->name }}</div>

            @endforeach

        </div>

        <div class="slider-icon right" onclick="scrollCategoriesRight()">

            <svg xmlns="http://www.w3.org/2000/svg" height="24" viewBox="0 0 24 24" width="24">

                <path d="M0 0h24v24H0V0z" fill="none"/>

                <path d="M8.59 16.59L13.17 12 8.59 7.41 10 6l6 6-6 6z"/>

            </svg>

        </div>

    </div>

    <div class="banner">

        <img src="{{ URL::asset('home\_assets/images/banner.png') }}" alt="" srcset="">

    </div>

    <div class="container-fluid" id="videoListContainer">

        @if (empty($videos))

            <div class="card text-center my-4">

                <p class="text-center py-4">No videos found</p>

            </div>

        @else

        <div class="row">

            @foreach ($videos as $video)

                <div class="col-sm-6 col-md-3 col-lg-3 vid-list my-3">

                    <a href="{{ route('playVideo', $video->slug) }}"><img src="/{{ htmlentities($video->thumbnail) }}" class="thumbnail"></a>

                    <div class="flex-div">

                        <img src="{{ isset($video->user->profile\_img) ? asset('profile\_photos/'.$video->user->profile\_img) : asset('/assets/images/users/avatar-9.png') }}" class="review-user-picture rounded-circle">

                        <div class="vid-info">

                            <a href="{{ route('playVideo', $video->slug) }}">{{ $video->title }}</a>

                            <p>{{ $video->user->name }}</p>

                            <p>{{ $video->comments\_count }} Comments</p>

                            <div class="review-rating">

                                @for ($i = 1; $i <= 5; $i++)

                                    <span class="star {{ $i <= $video->average\_rating ? 'filled' : '' }}">★</span>

                                @endfor

                            </div>

                        </div>

                    </div>

                </div>

            @endforeach

        </div>

        @endif

</div>

<script src="https://code.jquery.com/jquery-3.7.0.js"></script>

<script src="https://cdn.jsdelivr.net/npm/sweetalert2@11/dist/sweetalert2.min.js"></script>

<script src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.3/dist/js/bootstrap.bundle.min.js" integrity="sha384-YvpcrYf0tY3lHB60NNkmXc5s9fDVZLESaAA55NDzOxhy9GkcIdslK1eN7N6jIeHz" crossorigin="anonymous"></script>

</body>

</html>

1. **result observed**

A screenshot of a computer

Description automatically generated

*Figure 19: 360-degree video Platform Home Page*

A screenshot of a video

Description automatically generated

*Figure 20: 360-degree Video Streaming*

A screenshot of a computer

Description automatically generated

*Figure 21: Feedback and Video Recommendations*

A screenshot of a computer

Description automatically generated

*Figure 22: 360-degree video Storage*

A screenshot of a computer

Description automatically generated

*Figure 23: Feedback analysis*

A screenshot of a computer

Description automatically generated

*Figure 24: Admin Dashboard*

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