Audi Eyes

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# 1. Project Inception

## 1.1. Framing the Business Idea as an ML Problem

* Business case description

Audieyes is a pioneering project applying cutting-edge machine learning technology to improve visually impaired people’s quality of life and safety. It uses image and video captioning technology to provide immediate, comprehensive descriptions of surroundings and objects, virtually addressing accessibility or navigation issues. However, the software is a response to a severe problem that has received little attention from the massively underrepresented assistive programs market; it can have an enormous social and business impact. Audieyes technology helps companies enter new markets while ensuring its users get a massive improvement in their quality of life. Find more details here. For more details click [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#business-case).

* Business value of using ML

Machine learning can enhance the quality and customize recognition of the visual data. Such a possibility will promote the service in its capacity to help the visually impaired. Because of ML, the precise and fast captioning of the images and videos will be possible, providing real-time feedback required for an improved experience of navigation and interaction. Additionally, learning through usage and feedback modifications the service’s effectiveness, ensuring that the technology advances to fill all needs of different users. As a result, the users become dependent and more satisfied with the service, while the company becomes a leader in the innovation of similar technologies and extends market shares. Therefore, more users are likely to purchase the additional technology, ensuring the revenue streams. For more details click [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#business-value-of-using-ml).

* Data overview

Audieyes uses a large dataset consisting of image-text pairs obtained from COCO, flickr30k, vqa, and nlvr. This diverse set of information and illustrative situation scenarios are specifically important as it allows for more effective training of the ML models to better interpret and verbalize the image contents. The actual data refers specifically to common objects, people, sceneries, and actions, which guarantees the broad coverage and practical relevance of the encounters the visually impaired may expect. Such a broad data foundation ensures the contextual and semantic relevancy of the captions produced by the ML models, which is essential for the effective performance of the Audieyes system. For More details click [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#data-sources).

|  |  |  |
| --- | --- | --- |
| Model checkpoints | Dataset trained on | Pretrained model |
| model\_base.pth | N/A | N/A |
| model\_base\_nlvr.pth | https://storage.googleapis.com/sfr-vision-language-research/datasets/nlvr\_train.json | https://storage.googleapis.com/sfr-vision-language-research/BLIP/models/model\_base\_nlvr.pth |
| model\_base\_retrieval\_coco.pth | https://storage.googleapis.com/sfr-vision-language-research/datasets/coco\_karpathy\_train.json | https://storage.googleapis.com/sfr-vision-language-research/BLIP/models/model\_base\_retrieval\_coco.pth |
| model\_vqa.pth | https://storage.googleapis.com/sfr-vision-language-research/datasets/vqa\_train.json | https://storage.googleapis.com/sfr-vision-language-research/BLIP/models/model\_base\_vqa\_capfilt\_large.pth |
| model\_base\_retrieval\_flickr.pth | https://storage.googleapis.com/sfr-vision-language-research/datasets/flickr30k\_train.json | https://storage.googleapis.com/sfr-vision-language-research/BLIP/models/model\_base\_retrieval\_flickr.pth |

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* Project archetype

Audieyes represents a hybrid of autonomous real-time systems and human-in-the-loop architectures. It combines the speed and scalability of automated machine learning for instant image and video captioning with the precision of human oversight to enhance accuracy and contextual relevance. This model ensures that the system can operate independently while still benefiting from periodic human intervention to refine outputs, making it highly effective for applications in dynamic and varied environments. The design caters specifically to the needs of the visually impaired, promoting independence through technology while maintaining the flexibility to adapt and improve with user feedback. For more details click [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#architectural-archetypes-for-vision-captioning).

## 1.2. Feasibility analysis

* + literature review

The development of "Audieyes" is underpinned by significant advancements in machine learning, particularly in the fields of image and video processing that cater to enhancing accessibility for visually impaired individuals. This literature review examines the relevant technologies and models that form the basis of the Audieyes project, focusing on their applicability and effectiveness in real-world scenarios.

1. **. Machine Learning Models for Image and Video Captioning**
   1. **. Salesforce's BLIP Model:**

The BLIP (Bootstrapped Language Image Pretraining) model from Salesforce is a cornerstone in the image captioning domain, known for its efficacy in generating accurate and contextually relevant descriptions from images. BLIP’s architecture is designed to leverage large-scale datasets combining images with textual annotations, which is ideal for the diverse inputs expected in Audieyes. This model's proven capabilities in visual question answering and image captioning provide a reliable foundation for developing Audieyes’ core functionalities.

* 1. **. Moondream:**

Moondream is a compact, open-source computer vision model characterized by its portability and efficiency. Its design allows it to run on a wide range of devices, making it particularly suitable for real-time applications in accessibility technologies. The model’s robust performance in various settings demonstrates its potential to be integrated into Audieyes, ensuring that the application is both scalable and adaptable across different hardware environments.

* 1. **. Hugging Face’s Vit-GPT2 Image Captioning:**

Hosted on the Hugging Face platform, the Vit-GPT2 model combines vision-transformer (ViT) and GPT-2 technologies to create a potent image-to-text system. This model excels in translating visual data into descriptive text, a key feature for Audieyes. The use of transformer architectures allows for nuanced understanding and generation of captions, which can significantly enhance the user experience for the visually impaired by providing detailed and accurate descriptions of their surroundings.

* + Model choice/ specification of a baseline

For the Audieyes project, we have chosen the BLIP (Bootstrapping Language-Image Pre-training) model as our baseline due to its comprehensive abilities in both vision-language understanding and generation, which are essential for real-time image and video captioning applications aimed at assisting visually impaired users.

**Key Features and Specifications of BLIP:**

**Architecture:** BLIP employs a Multimodal Mixture of Encoder-Decoder (MED) architecture, which is versatile in functioning as a unimodal encoder, an image-grounded text encoder, or an image-grounded text decoder. This flexibility allows it to adaptively handle various tasks, including image captioning and text retrieval, within the same framework.

**Pre-training Methodology:** BLIP uses a novel dataset bootstrapping technique, CapFilt, which involves generating synthetic captions for web images and filtering out noisy ones. This method improves the quality of training data, especially considering the prevalent noise in web-crawled datasets.

**Performance Metrics:**

**Image-text retrieval:** Improved recall@1 by +2.7% on average.

**Image captioning:** Enhanced CIDEr scores by +2.8%.

**Visual Question Answering (VQA):** Increased VQA score by +1.6%.

**Generalization:** BLIP demonstrates strong zero-shot generalization to video-language tasks, which could be beneficial for extending Audieyes to video captioning in the future.

**Advantages for Audieyes:**

**High Relevance and Accuracy:** BLIP's capability to generate contextually relevant captions directly supports the core functionality of Audieyes, enhancing the user's understanding of their surroundings.

**Scalability and Flexibility:** The model’s architecture and the CapFilt training approach allow for easy scalability and adaptation to various data environments, crucial for deployment across different geographic locations.

* + Metrics for business goal evaluation

To effectively measure the success and impact of the Audieyes project, it is essential to establish clear, quantifiable metrics that align with the business objectives and operational goals. The following metrics have been identified to evaluate the performance and business value of Audieyes:

**1. User Engagement Metrics:**

**. Daily Active Users (DAU) and Monthly Active Users (MAU):** These metrics will help track the usage frequency and retention of the application, providing insights into its acceptance and value to users.

**. Session Length:** Measures the average duration users interact with the app per session, indicating the application's utility and user reliance.

**2. Performance Metrics:**

**. Caption Accuracy:** Accuracy of the image and video captions generated by the BLIP model, assessed through human validation or comparison with benchmark datasets.

**. System Latency:** Time taken from image/video input to caption output, crucial for real-time performance. A lower latency ensures a seamless experience for users.

**3. Customer Satisfaction Metrics:**

**. Net Promoter Score (NPS):** This metric gauge’s user satisfaction and likelihood to recommend Audieyes to others, which is pivotal for organic growth in the consumer base.

**. User Feedback and Reviews:** Qualitative assessments from users, providing insights into the app's impact on their daily lives and areas needing improvement.

**4. Accessibility Impact Metrics:**

**. Tasks Completed:** The number of tasks users successfully complete with the aid of Audieyes, such as navigation in new environments or identification of objects.

**. Incidence of Accessibility Issues:** Tracking issues reported by users related to accessibility, helping to refine and enhance the app’s functionality.

**5. Economic Metrics:**

**. Customer Acquisition Cost (CAC):** The cost associated with acquiring a new customer, essential for evaluating the efficiency of marketing strategies.

**. Lifetime Value (LTV):** The total revenue expected from a typical customer over the life of their relationship with the app, indicating the long-term viability of the project.

# 2. ML Pipeline Development - From a Monolith to a Pipeline

## 2.1. Ensuring ML Pipeline Reproducibility

* Project structure definition and modularity

The Audieyes project is organized into a modular architecture in order to optimize scalability, minimize maintenance costs and promote development team cooperation. This model is comprised of several layers: the Data Layer, the Model Layer, the Service Layer and the Application Layer. The Data Layer is tasked with receiving, preprocessing and storing data, ensuring data integrity and availability across the system. The Model Layer contains the machine learning models, including the baseline BLIP model and any supplementary models for specific tasks. The Service Layer is the intermediary between the model output and the application layer, efficiently redirecting API requests and outputs from the model. The Application Layer consists of the user-facing frontend interface as well as the backend application code that has user functionality, such as data visualization.

The division into these layers is reasonable since each of them is implemented as a relatively independent module with clearly defined interfaces for communication with other modules. Thus, each module can be updated or replaced separately, which is the necessary condition for high-quality work under the continuous integration and deployment systems.

In addition, it makes parallel development possible, because different teams can develop different modules without interfering with each other. This significantly accelerates development and enhances the overall productivity of the process. At the same time, testing and maintenance become significantly less complex, because each module can be tested and maintained separately, lowering the risk of critical system failures. Finally, the structured approach further promotes reusability, benefiting future projects. Critical functionality can be extracted into sharable libraries or services, which would be utilized across the different parts of the project or multiple projects in the future.

To sum up, the described approach to building a structured, modular pipeline guarantees the reliability and reproducibility for the Audieyes, while also preparing the system for further growth, meeting the project’s overarching goals and long-term ambitions.

* Code Versioning

GitHub and Docker Hub are used for maintaining robust code versioning and management for the Audieyes project. GitHub is the main repository for all of the project codes including the application logic, machine learning models, and system configurations. It enables version control to keep track of all the changes, revert to the older state, and maintain branches for issue tracking, feature development, or bug fixing. It also enables collaborative features such as PR and code review to maintain the quality and uniformity of the codebase across the development cycle. On the other hand, Docker Hub is used for managing the Docker images of the project. It enables our development pipeline to produce consistent environments throughout each stage from development to production. The Docker images are managed with versioning on Docker Hub so that anyone from the team or the CI/CD pipeline can pull the right version of the environment to run the application without any hassle. Thus, it enables the reusability of the environment and reduces the “works on my machine” situation.

* Data versioning

For the Audieyes project, data versioning is managed through Data Version Control (DVC), which plays a crucial role in maintaining the integrity and reproducibility of the machine learning pipeline. DVC allows the team to track versions of data sets and models, ensuring that every experiment can be reproduced, and every model training session can be traced back to its data source. This tool integrates seamlessly with existing version control systems like Git, but it manages large data files and machine learning models that Git cannot handle efficiently.

Using DVC, changes to datasets are tracked in a manner similar to source code, which enables the team to pinpoint the exact data version used for specific training runs. This capability is vital for debugging and improving models, as well as for team collaborations, where consistency in data usage needs to be maintained across different members and potentially remote environments. DVC also supports data storage in remote locations, providing flexibility in how and where data is accessed and stored, crucial for handling large-scale datasets typical in machine learning projects like Audieyes.

* Experiment tracking and model versioning

Critical components in managing the machine learning lifecycle effectively. MLflow offers a centralized platform to monitor experiments, including tracking of parameters, metrics, and model artifacts across various stages of the ML pipeline. This functionality allows our team to compare different model versions objectively, facilitating the identification of the most effective configurations based on empirical data.

Model versioning in MLflow provides a systematic way to version and store models, ensuring that every iteration is cataloged and retrievable. This capability is crucial for rolling back to previous versions if needed and for auditing purposes, allowing us to maintain a detailed history of model development and changes over time.

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By integrating MLflow, the Audieyes project benefits from enhanced reproducibility and accountability in model development, enabling seamless transitions between model iterations and ensuring consistent results in deployment environments. This setup not only streamlines the development process but also supports robust testing and deployment strategies, crucial for delivering a reliable assistive technology solution.

* Setting up a meta store for metadata

In the Audieyes project, we've integrated MLflow to set up a meta store for efficiently managing metadata. MLflow's meta store centralizes and streamlines the storage of essential metadata such as model parameters, configurations, and experiment results. This setup not only enhances the reproducibility of our ML pipeline but also facilitates seamless access and analysis of metadata across the project's lifecycle. By using MLflow's meta store, we ensure robust management of metadata, enabling effective tracking of experiments and model versions, which is crucial for maintaining consistency and accelerating development cycles in our Audieyes system. For more details click [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#experiment--metadata-tracking-with-mlflow).

* Setting up the machine learning pipeline under an MlOps platform

In the Audieyes project, we have set up our machine learning pipeline using ZenML, an open-source MLOps framework that enhances the entire lifecycle of machine learning from data ingestion to model deployment. ZenML supports our goal of developing and testing the ML pipeline with a structured and scalable approach, emphasizing reproducibility, collaboration, and automation. Our pipeline includes key components such as data validation to ensure the integrity of input data, data ingestion from diverse JSON sources, and data splitting to segregate data into training and validation sets effectively. Additionally, we use ZenML for training our models using the BLIP architecture for image captioning and rigorously evaluate model performance on the validation set to pinpoint areas for improvement. To ensure our models perform reliably and meet quality standards, we integrate GitHub Actions for running behavioral model tests, which automatically validate changes in the codebase and maintain high standards of functionality and performance. This comprehensive setup under ZenML not only streamlines our ML pipeline but also embeds best practices of MLOps, ensuring that the Audieyes project achieves its technological and business objectives efficiently.

View all the details of the pipline [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#milestone-4-ml-pipeline-development-and-testing).

## 2.2. Pipeline Components

* + 1. Setup of data pipeline within the larger ML pipeline/ MLOps Platform
  + Data Validation and Verification

For the Audieyes project, an integral component of our ML pipeline setup within the MLOps platform is the robust process of Data Validation and Verification. We utilize the library Great Expectations, which plays a critical role in ensuring the integrity and quality of data flowing through our pipeline. This tool allows us to implement comprehensive data checks, including schema validation, data type verification, and constraint checks, which help prevent data corruption and inconsistencies that could adversely affect model training and performance.

Great Expectations enables us to automate the validation process, providing a structured framework to define and verify expectations for data quality. This setup helps maintain a high standard of data quality from the ingestion phase through to model training, making our ML pipeline more reliable and efficient. By embedding Great Expectations into our data pipeline, we ensure that all data meets the predefined criteria before it is processed, enhancing the reliability of our ML outputs and ensuring that the Audieyes project delivers accurate and impactful results to the end-users. View details [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/Audieyes/zemML/pipelines/validation/greate_expectation_validation.ipynb).

* + Feature Engineering store

In the Audieyes project, preprocessing and feature engineering play a critical role in preparing data for effective machine learning model performance. We employ Apache Cassandra as our feature store to manage and serve features due to its exceptional scalability, fault tolerance, and high availability, which are essential for handling extensive volumes of feature data. Our preprocessing steps involve transforming raw data into a structured format that is optimized for easy ingestion into Cassandra. This structured data is then meticulously engineered to extract meaningful features that significantly enhance the model's ability to learn and make accurate predictions. By integrating Apache Cassandra into our ML pipeline, we ensure seamless access to up-to-date feature data for continuous training and inference, thereby enhancing the overall efficiency and effectiveness of our AI models in the Audieyes project. View details here.

* + 1. Integration of model training and offline evaluation into the ML pipeline / MLOps Platform

I have used Automated tests in the pipeline to automatically run. View the file [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/.github/workflows/deployment.yaml).  
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* + 1. **Development of model behavioral tests**

I have used GitHub Actions for running behavioural model tests. These tests validate the functionality and performance of the image captioning model, ensuring that it meets the specified requirements and quality standards. The tests are executed automatically whenever changes are made to the model codebase, providing continuous feedback on the model's behavior and performance.

**1. Model checkpoints Test:** the test checks that the model checkpoints are generated correctly and contain the expected parameters and metadata. check the test [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/Audieyes/zemML/tests/checkpoints_tests.py).

**2. Business Metrics Test:** the test evaluates the model's performance against predefined business metrics, such as operational efficiency, revenue and more. check the test [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/Audieyes/zemML/tests/metrics_tests.py)

**3. Model Deployment**

For the deployment phase of the Audieyes project, we have strategically chosen Docker, Linode, and Kubernetes to ensure a robust and scalable deployment of our machine learning models. Docker containers are utilized to package the AI models along with their dependencies, ensuring consistency across different computing environments from development to production. This containerization facilitates the easy management of model deployments and versioning, allowing for quick updates and rollbacks without disrupting the entire system.

We deploy these Docker containers on Linode, a cloud hosting provider known for its simplicity and high performance. Linode enables us to scale our resources according to demand efficiently and ensures our application remains available with minimal downtime. This flexibility is particularly beneficial for handling the varying loads our service may experience as user numbers grow.

Kubernetes plays a crucial role in orchestrating these containers. It manages the deployment and scaling of our application, ensuring that we can seamlessly shift traffic between different model versions based on their performance. This orchestration is vital for maintaining high availability and performance, as Kubernetes can dynamically manage the application's load and distribute resources optimally across the containers.

Together, Docker, Linode, and Kubernetes form a powerful trio that underpins our model deployment strategy, ensuring that Audieyes delivers a reliable, scalable, and efficient service to assist the visually impaired community.

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## 3.1 ML System Architecture

* Drawing with architecture highlights

A diagram of a flowchart

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This architecture diagram outlines the workflow and interaction of various technologies in the deployment and operation of the Audieyes project. Here's a breakdown of each component and their interconnections:

1. React App: This is the front-end interface where users interact with the system. It sends HTTP requests to the deployed model and receives responses that are displayed to the user.
2. Deployed Model: This is the core AI model that processes incoming requests from the React app. It's responsible for executing the model's logic of image captioning.
3. Linode Server: Hosts the deployed model. It's the compute environment where the model runs and interacts with other components.
4. GitHub Actions: Used for continuous integration and deployment (CI/CD/CT). It automatically pulls the latest version of the model from the repository, builds it if necessary, and deploys it to the Linode server.
5. Kubernetes: Orchestration platform that manages the deployment of different model versions on the server. It ensures that the system scales efficiently and handles load balancing and auto-scaling.
6. Database: Stores and manages data, including user data, model inputs & outputs, and application logs. It's used by the system for persistent storage and retrieval of data needed for model validation and other processes.
7. Grafana: Monitors the model and system performance. It pulls metrics from the deployed model and other parts of the system to visualize performance and operational data.
8. Cassandra: Acts as the feature store. It stores and manages the features used by the machine learning models, enabling efficient feature retrieval for model training and inference.
9. MLflow: Manages the machine learning lifecycle, including experiment tracking, model versioning, and model storage. It saves trained models and interacts with other components to facilitate model deployment and monitoring.
10. Airflow: Automates and manages workflows, such as data preprocessing and feature engineering. It ensures that data is processed and made available to MLflow and Cassandra in the correct format.
11. Great Expectations: Validates and verifies data quality, ensuring that the data used throughout the system meets defined expectations before it's processed and used in model training.
12. DVC (Data Version Control): Manages and versions datasets, facilitating reproducibility of experiments and providing a mechanism to roll back to previous data versions if needed.

### Workflow:

* The React App sends a request to the Deployed Model for processing.
* The Deployed Model, hosted on a Linode Server and managed by Kubernetes, processes the request and sends back a response.
* The response data is stored in a Database and also sent back to the React App for display.
* Grafana monitors the system, using metrics from the model and other components.
* GitHub Actions deploys updates to the model automatically.
* MLflow manages the lifecycle of the model, saving new versions and tracking experiments.
* Cassandra stores features that are retrieved by Airflow during data processing tasks.
* Great Expectations ensures the data quality before it's processed and used.
* DVC manages the data versions used across the system, ensuring consistency and reproducibility.

## 3.2 Application development

* Model service development

In the Audieyes project, the development of the model service is crucial for integrating and efficiently serving our machine learning models within the application's architecture. This involves encapsulating the models within a service layer, designed to facilitate seamless interactions between the React frontend and the complex machine learning operations. The service layer effectively manages requests from the frontend, processes these through the deployed models, and ensures timely and accurate responses.

To enhance scalability and reliability, we employ Kubernetes to orchestrate the deployment and operation of these model services. Kubernetes allows us to manage multiple instances of the model service dynamically, handling load balancing and ensuring that the system scales effectively under different load conditions. Crucially, Kubernetes also plays a pivotal role in model performance management by monitoring various model versions in production and seamlessly routing traffic to the best-performing models based on predefined metrics. This capability not only improves the overall system performance but also enhances user satisfaction by providing the most accurate and efficient responses.

The integration of CI/CT/CD practices using tools like GitHub Actions ensures that updates, whether they are new model versions or application updates, are consistently deployed to the Kubernetes-managed services without downtime. This robust setup forms the backbone of the Audieyes application development, ensuring it delivers high performance, reliability, and a seamless user experience. View Details [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#api-documentation).

* Front-end client development

The development of the front-end client is centered around React, a popular JavaScript library known for its efficiency and flexibility in building interactive user interfaces. We chose React because it enables the creation of a responsive and dynamic experience for users, essential for our application which requires real-time updates and interactive features. The React app is designed to be user-friendly, providing visually impaired users with an intuitive interface that allows easy interaction with the image and video captioning features. This front-end client communicates seamlessly with the back-end services through RESTful APIs, fetching data and displaying results efficiently. The use of React also facilitates the rapid development of new features and easy maintenance of the codebase, thanks to its component-based architecture and the wide ecosystem of development tools and libraries available. View Details [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/Audieyes/app/react_app/README.md).

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## 3.3 Integration and Deployment

* Packaging and containerization

The integration and deployment are streamlined through the use of packaging and containerization. We utilize Docker, a leading containerization technology, to package our application and its dependencies into lightweight, portable containers. This approach ensures consistency across development, testing, and production environments, eliminating the "it works on my machine" problem. Docker containers can be easily deployed on any system that supports Docker, regardless of the underlying infrastructure, which simplifies deployment and scaling operations. This method not only enhances the reproducibility of our application but also aligns with modern DevOps practices, allowing for rapid, reliable, and continuous deployment cycles facilitated by Kubernetes, which orchestrates container deployment, scaling, and management. View details [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/Audieyes/docker/README.md).

* Integration with a CI/CD Pipeline

For the Audieyes project, integration with a CI/CD pipeline is implemented using GitHub Actions to automate the build, test, and deployment processes. This setup ensures that every pull request or push triggers a series of actions that maintain the code quality and deployment readiness of our application. The CI/CD pipeline is composed of multiple jobs, starting with linting and testing where the code is checked for style and functionality issues. Node.js and Python environments are set up for respective dependencies and testing routines.

Post-validation, the train\_evaluate\_deploy job kicks in, which is contingent upon successful linting and testing. This job handles the model training, evaluation, Docker image creation, and pushing the image to a Docker registry. Finally, the trained model is deployed to a Linode server using SSH, where it's pulled and run inside a Docker container to ensure consistent execution environments. This CI/CD pipeline not only automates the workflow but also ensures that each component of our application is tested and deployed systematically, reducing human error and speeding up production cycles. View details [here](https://github.com/AyoubMaimmadi/Audieyes/blob/main/.github/workflows/deployment.yaml).

* Hosting the application

For hosting the Audieyes application, we utilize Linode, a cloud hosting service known for its reliability and scalability. Linode provides a robust infrastructure that allows us to deploy our containerized application components, managed by Kubernetes, ensuring efficient load balancing, auto-scaling, and seamless deployment of updates. This setup guarantees high availability and performance, essential for delivering continuous service to our users. The choice of Linode as our hosting solution supports our needs for a flexible and cost-effective cloud environment, enabling us to maintain optimal service levels as user demand and system complexity grow. View details [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#3--ml-service-deployment-and-model-serving).

## 3.4. Model Serving and online testing

* Model serving runtime

Model serving and online testing are streamlined through a robust model serving runtime. This setup involves deploying our machine learning models within a Linode server environment that can handle requests in real time, ensuring that users receive immediate and accurate responses. The models are hosted on servers configured with the necessary computational resources to perform at scale, and they are accessible through a well-defined API that allows the React front-end to interact seamlessly with the model serving backend.

For online testing, we implement techniques such as A/B testing and canary releases, facilitated by our use of Kubernetes for orchestration. This approach allows us to continuously evaluate different versions of our models under real-world conditions, ensuring that only the best-performing models are deployed to all users. This dynamic testing and deployment strategy ensures that the Audieyes project remains at the forefront of technological reliability and accuracy, providing a dependable service to the visually impaired community.

* Serving mode (batch, on demand to a human, on demand to a machine)

The model serving approach is designed to cater to on-demand requests with a focus on delivering results directly to end-users, potentially with human intervention for verification or additional input when needed. This serving mode ensures that users receive real-time, accurate information with an option for human oversight to enhance reliability and trust in the system.

For the model serving runtime, we utilize a robust infrastructure that supports high availability and rapid response times. The deployment is managed through containerization with Docker, which allows the models to be served efficiently and scaled dynamically according to demand. This setup is orchestrated by Kubernetes, which manages the containers and ensures that the model serving runtime is always optimized for performance, handling load balancing and fault tolerance seamlessly. This combination provides a reliable and efficient environment for model serving, crucial for maintaining the responsiveness and accuracy required by the Audieyes application.

* Online testing (A/B Testing, Bandit)

Online testing, including A/B testing and Bandit algorithms, plays a crucial role in optimizing and ensuring the effectiveness of our machine learning models. We implement A/B testing to systematically compare different versions of our models or features using Kubernetes Services, directly measuring their impact on user experience and system performance. This approach helps us identify the most effective models or features based on real user interactions. Additionally, we use Bandit algorithms to dynamically adjust the traffic distribution among different model versions during the testing phase. This method not only accelerates the learning process about the best-performing models but also minimizes the risk and exposure from potentially less effective model variations. Both strategies are integrated seamlessly into our MLOps practices, allowing us to continually refine and enhance the Audieyes app.

# Monitoring and Continual Learning

## 4.1. Resource Monitoring

In the Audieyes project, resource monitoring is a vital component of our Monitoring and Continual Learning strategy, focusing on the efficient tracking and management of system resources to ensure optimal performance and reliability. We utilize Grafana and Prometheus for this purpose, where Prometheus continuously collects and stores metrics from various parts of our infrastructure, including server load, response times, and resource usage. Grafana then visualizes these metrics through dashboards that provide real-time insights into the system's health and performance.

This monitoring setup allows us to quickly identify and address potential bottlenecks or issues in the system, such as spikes in CPU usage or memory leaks, which could affect the user experience or system stability. By having detailed visibility into our resource utilization, we can make informed decisions about scaling and optimizing our application, ensuring that it remains responsive and stable under varying loads.

Moreover, the integration of monitoring tools into our Kubernetes-managed environment helps in automating some aspects of resource management, such as horizontal scaling based on predefined resource usage thresholds. This proactive approach to resource monitoring not only enhances system performance but also supports the continual learning aspect of our project by providing valuable data that can be used to refine and improve our models and infrastructure over time. View details [here](Milestone%207:%20Monitoring%20and%20continual%20learning).

## 4.2. Model Performance Monitoring or data distribution drift monitoring

Monitoring model performance and detecting data distribution drift are vital for ensuring the long-term reliability and accuracy of our machine learning models. To achieve this, we have implemented a comprehensive monitoring system using tools like Grafana and Prometheus. This system continuously tracks key performance indicators (KPIs) such as prediction accuracy, response times, and system throughput. Additionally, it monitors the distribution of incoming data to identify any significant drifts that might affect model performance.

By setting up alerts and thresholds within Grafana, we can proactively respond to any anomalies or performance degradations detected. This proactive monitoring allows us to maintain the system's integrity and effectiveness, ensuring that the models continue to perform well even as input data evolves over time. This approach not only helps in maintaining high standards of service for the end-users but also supports the ongoing improvement and tuning of models, keeping them aligned with the latest data trends and user needs. View details [here](Milestone%207:%20Monitoring%20and%20continual%20learning).

## 4.3. Continual Learning: CT/CD pipeline

We've implemented a Continual Learning (CL) pipeline integrated with Continuous Training (CT) and Continuous Deployment (CD) to ensure our models adapt to new data and evolving user needs effectively. This pipeline automates the process of retraining models on fresh data, evaluating their performance, and deploying improved versions without manual intervention. We utilize Apache Airflow to manage workflow automation, orchestrating tasks like data ingestion, preprocessing, model training, and validation. Once a new model version meets our performance criteria, it is automatically deployed to production using Kubernetes, which manages the rollout and ensures that there is no downtime or disruption to the service. This setup supports a dynamic learning environment where our models continually evolve and improve, maintaining high accuracy and relevance in real-world applications. View details [here](https://github.com/AyoubMaimmadi/Audieyes?tab=readme-ov-file#1--ml-system-architecture).

## 4.4. Pipeline Orchestration

Pipeline orchestration is managed using Apache Airflow, which orchestrates complex workflows and ensures that each step of the machine learning pipeline, from data ingestion to model training and deployment, is executed in a timely and orderly manner. Airflow provides the flexibility to schedule and monitor workflows, handling dependencies and managing the execution of tasks across different stages of the pipeline. This automation not only streamlines operations but also enhances the reliability and efficiency of the entire system, allowing for scalable management of tasks and ensuring that resources are optimally utilized. By leveraging Airflow for pipeline orchestration, we ensure that the Audieyes project can maintain its operational efficiency and adapt quickly to new requirements as they arise.

# 5. Responsible AI

## 5.1 Evaluation Beyond Accuracy

* Audit Model for Bias

Recognizing the imperative of Responsible AI, we extend our evaluation beyond mere accuracy metrics to include comprehensive audits for bias in our models. This is crucial as the system is designed to assist a diverse group of visually impaired users, making it essential that the model's outputs do not favor one demographic over another.

To conduct effective bias audits, we employ a variety of techniques. First, we analyze the training data to ensure it represents a diverse range of scenarios and user groups, minimizing the risk of ingraining historical biases into the model. Next, we use statistical methods to detect any disparities in model performance across different groups defined by sensitive attributes like age, gender, and ethnicity.

We also implement fairness-aware machine learning algorithms that are designed to reduce bias by adjusting the model’s decision boundaries during training. To supplement these efforts, we engage with external audit teams who perform independent evaluations of the model to uncover any residual biases.

The findings from these audits inform continuous improvements in our training methodologies and model updates, ensuring that Audieyes remains a fair and equitable tool that enhances accessibility for all users, irrespective of their background. This commitment to auditing for bias underscores our dedication to upholding the principles of Responsible AI throughout the lifecycle of the project.

* Model Explainability and Interpretability

We prioritize model explainability and interpretability to ensure transparency and trustworthiness of our AI systems. This involves implementing techniques that make the inner workings of our machine learning models accessible and understandable to both technical and non-technical stakeholders. We utilize methods such as feature importance scores and model-agnostic tools like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) to elucidate how different features influence predictions. This approach not only helps in debugging and refining the model by identifying which features are most impactful but also aids in communicating the reasoning behind model decisions to end-users. Enhancing interpretability is crucial for maintaining user trust and for meeting regulatory and ethical standards, ensuring that our technology remains accountable and its decisions justifiable.

# 6. Conclusion

* Summary of Achievements

In conclusion, the Audieyes project has made significant strides in enhancing accessibility for the visually impaired community through innovative technology. We've successfully integrated advanced machine learning models, like Salesforce's BLIP, into a user-friendly application, providing real-time, accurate descriptions of the visual world. Our deployment strategy using Docker, Linode, and Kubernetes has ensured that our services are both scalable and reliable.

The project not only stands as a testament to technological innovation but also reflects our commitment to inclusivity and responsible AI. Through rigorous bias audits and continuous improvement, we ensure that our solutions are equitable and accessible to all users. Overall, Audieyes represents a major leap forward in making every day navigation and interaction more accessible for those with visual impairments, truly embodying the potential of technology to transform lives.

* Lessons Learned

Throughout the development of the Audieyes project, several key lessons have been learned that have significantly shaped our approach and execution. One of the foremost insights was the importance of user-centered design in creating technology for visually impaired users. Early user feedback highlighted that what developers assumed would be intuitive was not always the case for the end users, underscoring the need for iterative design and frequent user testing to ensure the technology truly meets the needs of its intended users.

We also learned the critical role of robust data management, particularly in ensuring data quality and diversity. Initial models showed biases because the training datasets were not representative of the diverse range of users who would interact with the system. This led to a comprehensive overhaul of our data collection and preprocessing stages, emphasizing the inclusion of a broader array of inputs to train more equitable and effective models.

Another significant lesson was about the scalability and flexibility of the technological infrastructure. As the project scaled, the initial setups struggled to handle increased loads efficiently. Adopting a microservices architecture, leveraging cloud services like Linode, and orchestrating our services with Kubernetes allowed us to manage scaling more dynamically and maintain performance regardless of user demand.

These lessons have not only improved the Audieyes project but have also provided valuable insights that we can carry forward into our future thesis work but this time using the approach of LLMs, ensuring we build more performing, scalable, and unbiased AI projects.

* Future Directions

As we look to the future of the Audieyes project, there are several exciting directions we aim to explore to enhance our system's capabilities and impact. One of the key areas we plan to delve into involves leveraging large language models (LLMs) to improve the descriptive accuracy and contextual relevance of our image and video captioning features. By integrating LLMs, we anticipate significant advancements in the system's ability to generate more natural and detailed descriptions, which will be particularly beneficial for visually impaired users in understanding their surroundings better.

Furthermore, we are considering the potential of expanding our technology to include predictive analytics, which could forecast potential obstacles or necessary actions based on the user’s environment and habitual patterns. This predictive feature could offer proactive assistance, enhancing safety and convenience for our users.

In addition to technical enhancements, we plan to use the Audieyes project as a cornerstone for our thesis. This will involve a detailed analysis of the implementation and impact of our system, emphasizing how innovative technologies like LLMs can revolutionize accessibility tools. Our thesis will document the challenges, solutions, and successes of developing Audieyes, providing a comprehensive case study on the application of cutting-edge AI technologies in real-world scenarios aimed at improving quality of life for individuals with visual impairments. This academic endeavor will not only contribute to our personal academic goals but also to the broader field of AI and accessibility, showcasing practical implementations and the transformative potential of AI.

# References

Junnan Li, D. L. (2022 , Jan 28 ). BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation.

# Appendices

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