WGU C951

Task 3

MACHINE LEARNING PROJECT PROPOSAL

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**A. Project Overview**

Recognizing that the safety of our drivers as well as the safety of everyone on the road is a top priority, the Research & Development Team at WeGovU Logistics proposes an innovative software solution designed to identify signs of WeGovU driver drowsiness by pulling real-time images from existing on-board driver cameras and assessing driver alertness during operation. Successful development and deployment of this solution would allow further integration of an alert system, enabling proper support channels to respond and provide potential crash intervention. This would enable WeGovU Logistics to mitigate risks associated with drowsy driving, decrease the number of crashes, and improve overall road safety.

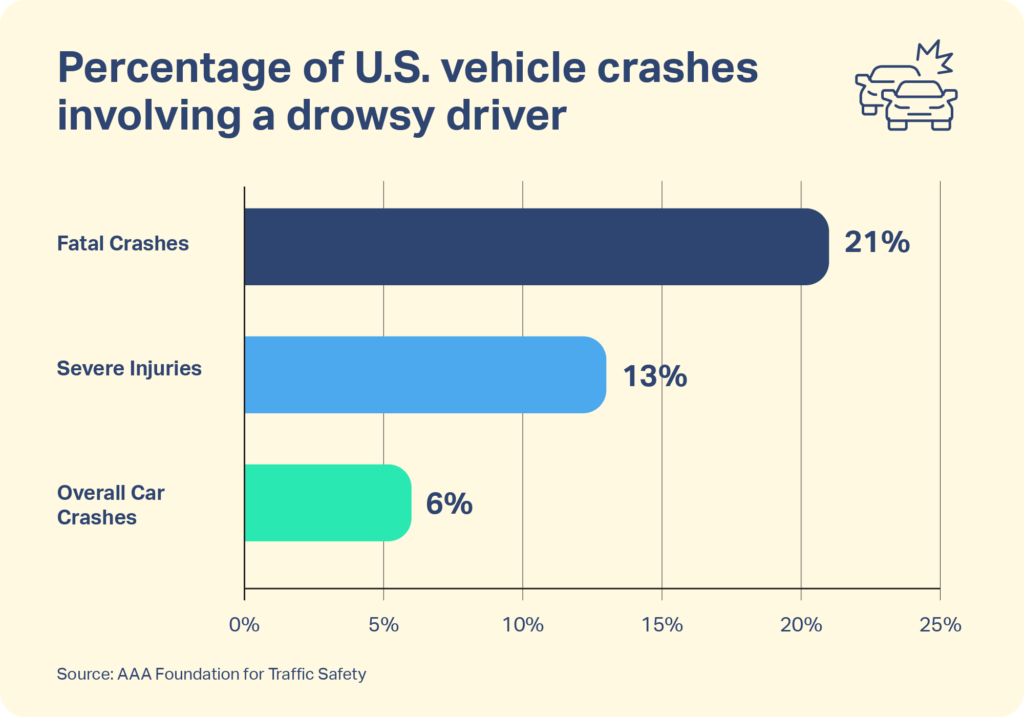
**A.1. Organizational Need**

WeGovU Logistics faces a significant challenge in dealing with the consequences of driver drowsiness, a plaguing issue in the transportation sector. To effectively address this challenge, the Research & Development team seeks the integration of innovative and effective drowsiness detection software, seamlessly blending with existing on-board driver cameras. This solution is designed to mitigate accidents stemming from fatigue not only prioritizing driver and traffic safety, but also reinforcing regulatory compliance, optimizing operational efficiency, and reducing costs linked to accidents and insurance. By proactively identifying and addressing signs of drowsiness through the integration of this software into existing onboard driver cameras, WeGovU Logistics aspires to cultivate a safer, more regulatory-compliant, and cost-efficient operational environment. This proposal outlines the imperative adoption of drowsiness detection software, strategically addressing both executive concerns and the practical needs of our tradespeople on the front lines.

**A.2. Context and Background**

WeGovU Logistics has been deeply rooted in the transportation sector for nearly 3 decades. The organization has a track record of proactively and intelligently investing in solutions that benefit the company and the community. The proposed software solution integrates machine learning to facilitate a strategic response to combat drowsy driving, which has historically been a plaguing issue in the industry.

How serious is drowsy driving? The AAA Foundation for Traffic Safety estimated a total of 328,000 crashes occurred due to driver drowsiness, accounting for 21% of all U.S. vehicle crashes. Out of those, approximately 109,000 resulted in injury and 6,400 were fatal. The National Highway Traffic Safety Administration estimated in 2021 that the cost of fatigue-related crashes resulting in injury or fatality cost society in general approximately $109 billion annually, not including property damage (National Safety Council).



Research reveals that although a significant majority of Americans acknowledge the peril of driving while drowsy (94.8%), nearly 19% of the surveyed individuals admitted to engaging in drowsy driving at least once within the past 30 days. Additional studies from AAA Foundation research in 2023 indicate that while drivers may recognize their drowsiness, they often underestimate its severity. Approximately 75% of individuals who believed they were only mildly fatigued were determined to be moderately or severely sleepy. Alarmingly, out of those drivers who acknowledged their fatigue, 75% opted to continue driving instead of pulling over for a break (Sleep Foundation).

Given the reported increase in police-reported traffic crashes from 5.25 million in 2020 to 6.10 million in 2021 (Stewart), it is reasonable to infer that the total number of crashes attributable to drowsy driving may have experienced a parallel rise. This concerning trend, coupled with a 16% increase, undoubtedly exacerbates an already problematic situation.

After assessing multiple strategies to address drowsy driving, WeGovU Logistics seeks to effectively minimize this risk by incorporating the proposed software solution. Notably, last-minute standalone interventions such as rumble strips have demonstrated an estimated 30-50% decrease in road departure crashes in rural settings (National Highway Traffic Safety Administration). Considering that rumble strips are more of a last-minute warning, WeGovU hopes to achieve similar rates of effectiveness by utilizing this solution as an earlier warning system, allowing more time for drivers to be alerted and corrective actions to be taken. With a workforce exceeding 11,000 drivers, WeGovU recorded 133 accidents in 2021, including 9 with fatalities. The implementation of an advanced early warning detection system is anticipated to further diminish the incidence of crashes attributed to driver drowsiness, improving driver and highway safety, and decreasing operational costs linked to crashes and insurance. Using the data from the National Safety Council, our target is a 10% decrease in overall crashes involving WeGovU drivers after the system is live. For comparison, a 10% decrease in accidents that involved WeGovU drivers in 2021 would save over $4 million in total costs as well as contribute to employee and community safety.

**A.3. Outside Works Review**

Our strategy is straightforward: utilize what resources are available. In our case, we possess onboard cameras and aim to enhance driver and community safety by detecting signs of driver drowsiness. Our process began with an examination of machine learning methods suitable for optimizing our existing onboard camera system. We meticulously refined our options until we identified the most fitting solution.

The article "10 Machine Learning Methods That Every Data Scientist Should Know" (Castanon) played a crucial role in establishing a foundational understanding of machine learning methods. This resource facilitated a swift narrowing down of potential methods by outlining the tasks each approach excels at. Simply put, we confirmed that the challenge at hand involves image classification, necessitating a supervised deep-learning neural network.

Recognizing that many solutions already exist for similar endeavors, we opted to adapt existing models rather than reinvent the wheel. Once we established the fundamental path for our solution, we delved into existing solutions to harvest insights into the most efficient ways to employ machine learning for monitoring and identifying drowsy drivers.

A review published on September 13, 2023, titled “A Deep-Learning Approach to Driver Drowsiness Detection” (Ahmed et al. 65) allowed us to further refine our approach by evaluating several other solutions mentioned in their work. Like their approach, we decided to utilize a public dataset from Kaggle.com for training and testing purposes, employing supervised classification. Using an existing dataset increases efficiency and saves substantial amounts of labor costs compared to collecting an image dataset from scratch.

In March 2020, the article “Driver Drowsiness Detection System using Machine Learning Algorithms” (Ramalingam et al.) presented a simple and effective solution relying solely on Computer Vision methodology, specifically the Haar Cascades algorithm. Applications leveraging computer vision incorporate input from various technologies, including sensing devices, artificial intelligence, and deep learning, to mimic the human vision system. These applications utilize algorithms trained on vast visual data to recognize patterns and apply them to discern the content of other images ("What is Computer Vision?"). Our solution will analyze and adopt a similar approach, tailoring the details to fit our specific application.

**A.4. Solution Summary**

Based on the observed success rates, WeGovU is optimistic that a customized approach, employing comparable techniques, will yield favorable outcomes. Our approach entails using computer vision methodologies to analyze images taken by onboard cameras, utilizing a supervised image classification convolutional neural network to ascertain whether the driver is experiencing drowsiness.

**A.5. Machine Learning Benefits**

By utilizing Kaggle.com as a training and testing dataset, our solution utilizes a convolutional neural network to classify drivers as drowsy or not. This approach enhances safety by addressing drowsy driving risks and providing our solution with a good baseline that continues to learn over time. The benefits of machine learning far outweigh the option of developing support staff to monitor approximately 11,000 drivers in real-time, considering the support staff would also be vulnerable to human error and distractibility. The solution enhances operational safety, leading to cost savings and a competitive edge. Post-deployment, ongoing improvement strategies include refining algorithms based on real-world feedback, updating training data, and incorporating advancements in machine learning technologies.

**B. Machine Learning Project Design**

**B.1. Scope**

The scope of this project is to develop a machine learning solution to detect signs of drowsiness by analyzing images captured from existing onboard cameras. This includes:

* Collecting the image dataset for training and testing
* Manually categorizing and verifying images as drowsy or not drowsy
* Develop an image classification AI to automate the identification of images as drowsy or not drowsy.
* Calibrate the image classification AI to achieve an optimal success rate.

Not included in this solution (but not limited to) are the following:

* Integrating an interface with the onboard satellite communications system to alert the dispatcher of driver status. This is due to the licensing agreement with the satellite communications service provider. Future upgrades to this solution include a prearranged collaboration with the provider for system integration to allow dispatch to be alerted of driver status, location, speed, and route history.
* Text recognition will not be included in this software solution. Any text found in images from onboard cameras is not factored into the image categorization process in this solution.

**B.2. Goals, Objectives, and Deliverables**

The primary goal of this project is to develop an image classification system that automates the identification and categorization of images as drowsy or not drowsy using machine learning. This is a proactive solution to contribute to employee and community safety, optimize operation efficiency, and decrease costs due to insurance and accidents.

**Goals**

* Develop an image classification system that automates the identification and categorization of images as drowsy or not drowsy using machine learning.
* Utilize the image classification system to contribute to employee and community safety by decreasing the number of accidents caused by drowsy driving.
* Decrease the number of accidents involving WeGovU drivers by 10%.
* Decrease operational costs directly related to accidents and insurance by 10%.

**Objectives**

* Establish and clean the dataset for training and testing.
* Develop image classification AI.
* Train image classification AI to categorize images as drowsy or not drowsy.
* Calibrate image classification AI to optimal rate.
* Achieve accuracy of 90%, with an error rate less than or equal to 10%.
* User testing survey scores to achieve 70% or higher with positive feedback.
* Future improvements – phase 2 will include collaboration with the onboard satellite communications provider to integrate communications with dispatch upon alert, relaying driver status, truck location, speed, and route history.

**Deliverables**

* Dataset for training and testing
* Image classification AI
* Accuracy rate of 90%
* Project documentation

Other deliverables include employee training to enable greater and more accurate utilization. This will allow the user to fine-tune the settings to achieve the most accuracy.

**B.3. Standard Methodology**

**SEMMA** is the strategic choice to elevate operational efficiency and deliver enhanced services required for this project. For this endeavor here are SEMMA's key stages:

1. **Sample:**
   * First, we acquire a sample dataset to establish the foundation of our machine learning model. This involves utilizing a set of stock photo images for rigorous training and validation.
2. **Explore:**
   * Next, we complete an in-depth exploration of the dataset. We analyze any relationships between data elements and identify potential gaps. This scrutiny allows a greater understanding of trends and patterns that may impact the precision of our model.
3. **Modify:**
   * In this phase, our focus shifts to refining the dataset for a seamless transition to the modeling stage. Here is also where we assess the need for any enhancements or transformations, including potential augmentation of the dataset by refining the images themselves to introduce greater diversity.
4. **Model:**
   * The modeling stage marks a critical juncture where sophisticated data mining techniques are employed to craft a predictive model aligning with the desired outcomes. In our case, this entails the selection of an appropriate image recognition model architecture, followed by rigorous training using the meticulously prepared dataset.
5. **Assess:**
   * Concluding the process, we subject the model to a meticulous evaluation of its reliability. The performance metrics are rigorously compared against the overarching objective of our project: the precise tagging of images based on their content.

The application of SEMMA ensures a methodical progression through each stage of our image recognition project. SEMMA promotes operational excellence and reinforces our commitment to deliver optimal outcomes.

**B.4. Projected Timeline**

**The projected timeline is an estimate. Actual**

**Start date: Description:**

January 29, 2024 The proposal is accepted and the project charter is established.

February 1, 2024 Proof of concept is presented.

February 5, 2024 Project Initiation.

March 13, 2024 Development begins.

April 1, 2024 User testing begins.

April 22, 2024 Deployment begins.

May 3, 2024 Finalized Reporting and Project Summary delivered.

**Sprint Schedule**

|  |  |  |  |
| --- | --- | --- | --- |
| **Sprint** | **Start** | **End** | **Tasks** |
| 1 | February 5, 2024 | February 9, 2024 | Project goals, roles, and stakeholders are clearly defined, and initial planning is established. |
| 1 | February 7, 2024 | February 9, 2024 | Backlog Refinement and Sprint Planning. |
| 2 | February 12, 2024 | February 23, 2024 | Acquire dataset for training and testing |
| 3 | February 26, 2024 | March 8, 2024 | Clean the dataset |
| 4 | March 11, 2024 | March 13, 2024 | Set up the development environment and tools. |
| 5 | March 13, 2024 | March 22, 2024 | Develop image recognition AI |
| 6 | March 25, 2024 | March 29, 2024 | Train, test, and calibrate the image recognition model. |
| 7 | April 1, 2024 | April 5, 2024 | Initial user testing |
| 8 | | April 8, 2024 | April 10, 2024 | Evaluate user feedback and test results. |
| 9 | | April 8, 2024 | April 19, 2024 | Fine tune the model and optimize operations. |
| 10 | | April 15, 2024 | April 19, 2024 | Verify solution meets project requirements. |
| 11 | | April 22, 2024 | April 26, 2024 | Begin deployment – image recognition AI to be deployed on predetermined groups in a structured sequence, with ongoing training. During deployment, system performance will be monitored and adjusted as needed to improve performance and accuracy in a live environment. |
| 12 | | April 29, 2024 | May 3, 2024 | Finalized reporting and project summary submitted. |

**B.5. Resources and Costs**

|  |  |  |
| --- | --- | --- |
| **Resource** | **Description** | **Cost** |
| Project Manager  Labor x 00 hours | Administration and Project Management duties | $20,000 |
| ML Engineer  Labor x 00 hours | Develops, trains, tests, and tunes image categorization AI | $40,000 |
| Cloud Hosting | Secure cloud storage for all data | $15,000 |
| Front End Development  Labor x 00 hours | Develops User Interface | $15,000 |
| Back End Development Labor x 00 hours | Develops back-end logic and architecture | $25,000 |
| Quality Assurance x 00 hours | Testing and verification. | $10,000 |
| Hardware | Additional costs for required hardware, hardware upgrades, GPUs, CPUs, storage, etc. | $65,000 |
| Software – ML Frameworks and Libraries, Dev tools, Database Software, Operating systems | Costs can vary depending on levels of support included with different providers ($0 - $20,000) | $20,000 |
| Legal | IP Rights, Compliance | $13,000 |
| Miscellaneous | Office supplies, IT supplies, etc. | $10,000 |
| Post Implementation | Maintenance, support, monitoring, updates | $20,000 |
| Contingency | Buffer | $38,000 |
|  | **Total** | $291,000 |

**B.6. Evaluation Criteria**

|  |  |
| --- | --- |
| **Objective** | **Success Criteria** |
| User ratings and feedback | User survey scores 70% or higher with positive feedback |
| Error rate | Incorrect image categorization score to be 10% or lower |
| Image categorization accuracy | Final testing to result in 90% or higher accuracy |

**C. Machine Learning Solution Design**

**C.1. Hypothesis**

Through the development and implementation of this solution, WeGovU aims to reduce the incidence of crashes involving its drivers by 10%. Utilizing data from the AAA Foundation for Traffic Safety and National Safety Council, WeGovU Logistics conducted an assessment of potential accidents caused by drowsy driving among its drivers. After evaluating various strategies to address this issue, WeGovU Logistics proposes this software solution to effectively mitigate the risk of drowsy driving.

Drawing inspiration from successful interventions, such as the deployment of rumble strips resulting in a 30-50% reduction in road departure crashes in rural settings (National Highway Traffic Safety Administration), WeGovU anticipates achieving similar effectiveness. The proposed solution acts as an early warning system, offering drivers more time for timely alerts and corrective actions.

With a workforce exceeding 11,000 drivers, WeGovU documented 133 accidents in 2021, including 9 with fatalities. Based on the data from the AAA Foundation for Traffic Safety and National Safety Council, a conservative 10% reduction in accidents involving WeGovU drivers in 2021 could yield savings exceeding $4 million in total costs, contributing significantly to employee and community safety.

The development and implementation of this solution will decrease the number of crashes involving WeGovU drivers by 10%. Additionally, it is expected to result in enhanced overall driver and community safety, and a reduction in operational costs associated with crashes and insurance.

**C.2. Selected Algorithm**

Several machine learning models were evaluated including Convolutional Neural Networks (CNNs), Logistic Regression, and Random Forest. Considering the complicated nature of binary facial image categorization, the WeGovU team selected supervised Convolutional Neural Networks as the best fit that would provide the greatest amount of accuracy looking forward.

**C.2.a Algorithm Justification**

When tasked with Image Recognition, Detection, and Classification, Convolutional Neural Networks (CNNs) stand out as a highly regarded choice. Functioning as a neural network architecture inspired by human neurons, CNNs demonstrate notable efficacy when trained on image data. Their approach involves a meticulous configuration of filters and convolution layers, allowing for the thorough processing of images. Navigating through these layers, CNNs generate a detailed feature map of the image, leveraging pixel representation and showcasing their proficiency in capturing intricate visual patterns (Kili Technology).

**C.2.a.i. Algorithm Advantage**

One advantage of CNNs, when compared to algorithms like Random Forest, is their inherent capability to autonomously learn hierarchical representations of features from images. This ability facilitates robust pattern recognition, particularly advantageous for tackling complex visual tasks. This automatic learning feature ensures adaptability to diverse image characteristics, enhancing the overall performance of the algorithm (Kumar).

**C.2.a.ii. Algorithm Limitation**

However, it is crucial to acknowledge a potential disadvantage of CNNs in comparison to the computational efficiency of Random Forest. CNNs may demand substantial computational resources, which can be a limiting factor, especially in resource-constrained environments or mobile applications with limited processing capabilities (Kumar).

Despite this drawback, the selection of CNNs for our proposal is warranted by their unparalleled excellence in handling image-related tasks. The ability to capture intricate patterns is crucial for our drowsiness detection application. The automated learning capability and adaptability to hierarchical features make CNNs the optimal choice, ensuring superior performance in image categorization and effectively addressing the specific requirements of our mobile application.

**C.3. Tools and Environment**

As with any job, proper tools and resources are required. Our solution taps into an existing Kaggle dataset to kickstart development. Essential requirements include a computer equipped with a robust CPU and GPU, ample RAM, and the use of Jupyter Notebooks for Python coding, all tracked with version control via Github. The project gains strength from Python libraries like NumPy, Pandas, Matplotlib, Seaborn, OpenCV, Scikit-learn, TensorFlow or PyTorch, and Keras. We also consider facial recognition APIs, such as Microsoft Azure or Google Cloud Vision API, and explore insights from third-party code on platforms like GitHub.

For interactive and visual coding, we turn to Jupyter Notebooks. To manage our development process effectively, we implement virtual environments, a requirements.txt file, and conduct unit testing. Consistent version control is maintained through regular Git commits, hosted on platforms like GitHub. Thorough documentation, including code comments, README files, and Jupyter Notebook markdown cells, ensures clarity across multiple disciplines. This student-friendly approach guarantees a collaborative and transparent development process, accommodating the diverse skill sets of team members from various disciplines.

**C.4. Performance Measurement**

Quality and performance will be measured by assessing the AI’s accuracy, specifically, the solution’s ability to correctly identify and categorize the images with minimal errors. Throughout development and testing, the team will continuously monitor performance levels to identify areas needing improvement and explore methods to increase accuracy. Please refer to the below table reviewing Performance Objectives and Success Criteria.

|  |  |
| --- | --- |
| **Performance Objective** | **Success Criteria** |
| User ratings and feedback | User survey scores 70% or higher with positive feedback |
| Error rate | Incorrect image categorization score to be 10% or lower |
| Image categorization accuracy | Final testing to result in 90% or higher accuracy |

**D. Description of Data Sets**

**D.1. Data Source**

This solution utilizes an existing dataset from Kaggle, consisting of 4000 images, to train the AI to correctly identify and categorize images as drowsy or not drowsy.

**D.2. Data Collection Method**

Kaggle is a platform for data science competitions and collaborative projects. Users on Kaggle may download and contribute to datasets shared by the community. The data available on Kaggle is diverse and can cover various domains, allowing users to download datasets for analysis, model training, and other data science tasks.

**D.2.a.i. Data Collection Method Advantage**

One significant advantage of using Kaggle for data collection is the availability of a wide range of datasets contributed by the global data science community. This diversity enables us to access existing high-quality datasets, saving valuable time and effort in sourcing data. Additionally, Kaggle datasets often come with documentation and discussions, providing valuable insights and context that can enhance the understanding of the data.

**D.2.a.ii. Data Collection Method Limitation**

A potential disadvantage is the lack of control over the data collection process and finding a dataset that satisfies project requirements. Kaggle datasets are contributed by various users, and the quality and reliability of the data may vary. Our solution must include careful evaluation and cleaning of the dataset intended for use, considering factors such as completeness, accuracy, and relevance to our goals.

**D.3. Quality and Completeness of Data**

To ensure proper data preparation, our solution structures the dataset to align optimally with the image recognition capabilities of the CNN, streamlining computational processes for efficient image analysis. An essential focus of this process is the meticulous monitoring of outlier images and edge cases and ensuring their accurate categorization and relevance. Quality and completeness of the data are paramount concerns and require expert scrutiny to ensure the dataset meets the necessary high standards for accuracy.

To prepare for this project, where we utilize an existing dataset obtained from Kaggle, we prioritize the quality and completeness of the data to ensure the robustness of our machine learning model. The following measures will be systematically implemented:

**a) Formatting Dataset from Kaggle:**

* Employ standardized formatting techniques to optimize the dataset's structure, ensuring compatibility with the image recognition capabilities of our Convolutional Neural Network (CNN).

**b) Addressing Missing Data, Outliers, Dirty Data, Null Values, Anomalies:**

* Implement thorough data cleansing processes to address missing values, outliers, dirty data, and anomalies, ensuring a clean and reliable dataset for model training.

**c) Time Origin of Data for Relevance:**

* Carefully assess the time origin of the data to guarantee its relevance, considering any temporal aspects that might impact the accuracy of our model.

**d) ETL (Extract, Transform, Load) for Data:**

* Execute a systematic ETL process to Extract, Transform, and Load the dataset, optimizing its structure for effective utilization in our machine learning model.

**e) Cleaning Data of PII (Personally Identifiable Information):**

* Prioritize the removal or anonymization of any Personally Identifiable Information (PII) to adhere to data protection standards and regulations.

**f) Relevance of All Data Fields in the Dataset:**

* Scrutinize and validate the relevance of all data fields within the dataset, ensuring that each contributes meaningfully to the objectives of our image recognition project.

**g) Uniformity Between Yes/No, True/False, On/Off Boolean Variables:**

* Standardize the representation of Boolean variables (Yes/No, True/False, On/Off) to ensure uniformity and avoid inconsistencies in the dataset.

**h) Keeping Data Current – Updating Regularly:**

* Establish a systematic process for regularly updating the dataset to reflect the latest information, ensuring that the model is trained on the most recent and relevant data.

This meticulous approach to dataset quality and completeness serves as the foundation for the success of our machine learning model, aligning with industry best practices and ensuring optimal performance in the recognition of driver drowsiness.

**D.4. Precautions for Sensitive Data**

In adherence to WeGovU's established policies and procedures governing the handling and storage of sensitive data, all WeGovU employees are bound by stringent guidelines. Furthermore, to fortify the security framework, non-disclosure agreements (NDAs) will be mandatory for all external stakeholders engaged in the project. While the Kaggle dataset utilized is publicly accessible and requires no specific safeguards, it is imperative to note that all data, including images captured and utilized throughout the project, is deemed confidential. This commitment to confidentiality is integral to ensuring the utmost security and privacy of the data involved in our initiative.

To further mitigate risks associated with managing and communicating about extensive sets of sensitive data within our project, additional precautions include:

a) **Security and Risk of Theft:**

* Prioritize the implementation of robust security measures to safeguard against unauthorized access or potential theft.
* Employ encryption protocols to bolster the protection of sensitive data during both storage and transmission.

b) **Loss of Data:**

* Implement rigorous backup and recovery procedures to mitigate the risk of data loss.
* Regularly conduct data integrity checks to promptly identify and rectify any anomalies.

c) **Corruption of Data:**

* Institute measures to ensure the integrity of the dataset, including regular validation checks and data cleansing procedures.
* Establish a clear protocol for addressing and rectifying data corruption issues promptly.

d) **Internal Theft (by Employees):**

* Enforce access controls and permissions, restricting data access solely to authorized personnel.
* Conduct periodic internal audits to detect and prevent potential unauthorized activities.

e) **Non-compete Agreements:**

* Require all external stakeholders engaging in the project to sign non-disclosure agreements (NDAs) to safeguard against unauthorized sharing or use of sensitive information.
* Clearly communicate the terms and consequences of non-compete agreements to all involved parties.

These proactive measures collectively contribute to the robust protection and ethical handling of sensitive data throughout the project's lifecycle, aligning with our commitment to confidentiality and compliance with industry standards.

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