WGU C964

MACHINE LEARNING PROJECT PROPOSAL

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**A. Project Overview**

Fine Canine Cuisine (FCC) stands as a premium dog nutrition establishment nestled in Crittenden County, Arkansas. Recently, FCC publicly announced its quest to enlist fresh talents through various social media platforms for the esteemed role of Fine Canine Ambassador. Each appointed Ambassador will be tasked with representing a specific category of dog nutrition products tailored to cater to the distinctive needs of various breeds.

The overwhelming response from our community resulted in a staggering 10,000 enthusiastic furry applicants. To meticulously select the ideal four-legged ambassadors, FCC is now in the process of categorizing each applicant's photo by breed. This meticulous categorization is crucial to facilitate the subsequent committee's task of choosing the most suitable candidate for each specialized product line.

The successful development and seamless deployment of this categorization solution are of paramount importance in ensuring that FCC's canine ambassadors align perfectly with the unique qualities of the products they represent.

**A.1. Organizational Need**

To address the organizational need, Fine Canine Cuisine (FCC) recognizes the essential requirement for a structured and efficient system to manage the overwhelming response of over 10,000 furry applicants vying for the coveted role of Fine Canine Ambassador. The need arises for a meticulous categorization process that will streamline the selection of ambassadors based on their respective breeds. This organizational challenge necessitates the development and implementation of a robust solution to handle the large volume of applications. The goal is to establish a well-organized framework that aligns with FCC's commitment to excellence, allowing for a seamless selection of canine ambassadors who will represent the diverse array of dog nutrition products offered by the company.

**A.2. Context and Background**

Fine Canine Cuisine has been a steadfast advocate for pet health and nutrition since 2016, demonstrating unwavering support for various local no-kill shelters in Crittenden County. Our primary objective is straightforward: to deliver the most delectable food with optimal nutritional profiles, sourced from organic ingredients, tailored to the diverse needs of different dog breeds. Over the years, Fine Canine Cuisine has consistently witnessed substantial year-over-year revenue increases, averaging an impressive 30% since 2016. As we strive for continued growth and heightened brand visibility, our exploration has led us to consider the advantages of appointing pet ambassadors for each product line.

Numerous companies, including Taco Bell with their chihuahua, Meow Mix featuring Morris the cat, Zynga with Zinga the American bulldog, and Weego the Bud Light Rescue Mutt, have successfully employed mascots as powerful representations of their brands. These mascots serve as memorable and endearing symbols, as highlighted in the "7 MVP (Most Valuable Pet) Brand Mascots: Past and Present." These iconic figures forge emotional connections with pet owners, contributing significantly to brand perception and recognition.

Whether in the form of a real dog or a fictional cat, these animal mascots play a pivotal role in shaping brand identity. A lovable pet ambassador or mascot enhances a company's visibility, leaving a lasting impression on consumers. Research, such as the insights shared in the "Ultimate Guide to Brand Ambassador Programs for Dog Owners," emphasizes the effectiveness of pet ambassadors in creating genuine and emotive connections. Pets possess a unique ability to foster emotional bonds between audiences and brands, and aligning products with charismatic pet influencers taps into universally cherished sentiments and positive associations associated with beloved furry companions, as noted by "Pets as Brand Ambassadors: Leveraging Influencers for Marketing Success."

The successful development and implementation of the proposed solution will streamline Fine Canine Cuisine's efforts in appointing Fine Canine Ambassadors, furthering our commitment to sustained revenue growth and enhanced brand recognition.

**A.3. Outside Works Review**

Our strategic approach revolves around maximizing available resources. Currently armed with a collection of over 10,000 customer-submitted dog images and a compact 2-person development team, our journey commenced with a thorough examination of machine learning methodologies that align with our objectives. We meticulously sifted through various options, refining our choices until pinpointing the most suitable solution.

Acknowledging the many existing solutions for similar ventures, we opted for an exploration of established models instead of reinventing the wheel. Our goal was to collect insights on the most efficient ways to leverage machine learning for our multiclass classification project within the confines of current FCC resources.

In the article "Novel Meta-Learning Techniques for the Multiclass Image Classification Problem," Vogiatzis et al. delve into decomposition-based strategies for multiclass image classification, proposing methods to optimize the ensemble phase, including a mixture of experts scheme and combining learner-based outcomes using Bayes’ theorem. While exhibiting improvements compared to baseline, factors such as resource availability and project deadlines prompted the team to persist in the quest for an even more fitting solution.

Another comprehensive project, "Deep Reinforced Active Learning for Multi-Class Image Classification" by Slade and Branson, integrates active learning, deep learning, and reinforcement learning. Despite noted accuracy improvements, the substantial resource requirements and slower processing speed rendered it unsuitable for our project.

"10 Machine Learning Methods That Every Data Scientist Should Know" by Castanon played a pivotal role in establishing a foundational understanding of machine learning methods. This resource facilitated a swift narrowing down of potential methods by outlining each approach's strengths. Confirming that the challenge at hand involves image classification, we determined that a supervised deep-learning neural network is imperative.

Lastly, in "Supervised Deep Learning for Multi-Class Image Classification," a Convolutional Neural Network (CNN) and Softmax model are employed (Zhou). The project applies these deep learning algorithms to a large-scale Multi-Class Image Classification dataset from the ImageNet annual competition. Despite reported hindrances due to hardware limitations, the development team at FCC believes that a scaled-down, simplified version utilizing a CNN represents the optimal choice for our machine learning solution.

**A.4. Solution Summary**

Based on the observed success rates, Fine Canine Cuisine is optimistic that a customized approach, employing comparable techniques, will yield favorable outcomes. Our approach entails using Computer Vision methodologies to analyze images submitted by customers, utilizing a supervised image classification convolutional neural network to classify the dog in each image by breed.

**A.5. Machine Learning Benefits**

In our proposed solution, we leverage a convolutional neural network to categorize dog images based on their breeds. This method significantly enhances the efficiency of the breed classification process, streamlining the selection of our Fine Canine Ambassadors. Opting for machine learning proves more advantageous than the alternative of deploying support staff to classify the extensive dataset of over 10,000 dog images accurately and efficiently, considering the potential for human error and distractibility. This solution not only leads to cost savings but also provides a competitive edge. Following deployment, our continuous improvement strategies involve refining algorithms based on real-world feedback, updating training data, and integrating 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 classify images of dogs by breed by analyzing images sent by their owners. This includes:

* Collecting the image dataset for training and testing
* Categorizing and verifying images by breed
* Develop an image classification AI to automate the identification of dog images by breed.
* 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 for mobile or digital image capturing devices.
* Text recognition will not be included in this software solution. Any text found in images will not be 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 categorization of dog images by breed using machine learning. This is a solution to streamline the process of selecting our new Fine Canine Ambassadors.

**Goals**

* Develop an image classification system that automates the and categorization of dog images by breed 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 dog images by breed.
* Calibrate image classification AI to optimal rate.
* Achieve accuracy of 90%, with an error rate less than or equal to 10%.

**Deliverables**

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

**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 dataset to establish the foundation of our machine learning model. This step has already been completed thanks to our loyal customers who sent in over 10,000 images.
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 \*DONE\* |
| 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 50 hours | Administration and Project Management duties | $5,000 |
| ML Engineer  Labor x 100 hours | Develops, trains, tests, and tunes image categorization AI | $10,000 |
| Cloud Hosting | Secure cloud storage for all data | $500 |
| Front End Development  Labor x 10 hours | Develops User Interface | $600 |
| Back End Development Labor x 20 hours | Develops back-end logic and architecture | $1,200 |
| Quality Assurance x 20 hours | Testing and verification. | $1,000 |
| Hardware | Additional costs for required hardware, hardware upgrades, GPUs, CPUs, storage, etc. | $0 |
| 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) | $2,000 |
| Legal | IP Rights, Compliance | $5,000 |
| Miscellaneous | Office supplies, IT supplies, etc. | $1,000 |
| Post Implementation | Maintenance, support, monitoring, updates | $10,000 |
| Contingency | Buffer | $6,000 |
|  | **Total** | $42,300 |

**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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