Gaurav Shukla

2022ac05280@wilp.bits-pilani.ac.in

Abstract

An AI powered cloud storage cleanup system that uses a fine-tuned model to categorize low value images and save cost.

Mid semester report

Image detection model for cloud cleanup and cost optimisation

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# Dissertation Abstract

Cloud storage plays a crucial role for both individuals and businesses by providing a flexible and scalable solution for managing digital assets. However, the accumulation of unorganized and redundant data can lead to increased costs and decreased efficiency, as storage space is consumed by unnecessary files. This project addresses these challenges by introducing a machine learning-based Image Detection Model designed to enhance digital storage management. The model is capable of identifying and categorizing images that are unused, duplicated, or of low value, such as screenshots, blurred photos, and other redundant files that occupy valuable storage space without contributing meaningful content. By utilizing advanced image recognition technologies, the system is able to classify images accurately and assign them a ranking based on factors like relevance, quality, and duplication. With these rankings, users are provided with actionable suggestions on how to optimize their storage usage. This strategic approach not only helps in reducing storage costs by eliminating unnecessary files but also aids in streamlining digital asset management, ensuring that users can maintain an organized and efficient digital library tailored to their specific needs. Through this innovative solution, individuals and businesses can maximize the utility of their cloud storage systems while minimizing expenditure and boosting operational efficiency.

# Literature Review

The initial phase of the project involved a comprehensive review of existing research in image detection, cloud storage optimization, and cost-reduction strategies. Examined several state-of-the-art image detection models, including ResNet, YOLO, and CLIP.

## Comparison of ResNet, YOLO, and CLIP:

### ResNet (Residual Networks):

* Strengths: ResNets excel at image classification tasks, especially for deep networks. The residual connections mitigate the vanishing gradient problem, allowing for the training of very deep architectures that can capture complex features. They consistently achieve state-of-the-art results on benchmark datasets like ImageNet.
* Weaknesses: ResNets are computationally expensive, requiring significant processing power and memory. This can make them less suitable for real-time applications or deployment on resource-constrained devices, although cloud deployment alleviates this to some extent. They primarily focus on image classification, not directly on object detection or image similarity analysis.

### YOLO (You Only Look Once):

* Strengths: YOLO is a real-time object detection system. Its speed and efficiency are major advantages. It can detect multiple objects within an image simultaneously, which could be useful for identifying duplicates or similar images.
* Weaknesses: YOLO's accuracy, particularly for smaller or occluded objects, can be lower than some other object detection methods. It may not be ideal for fine-grained image analysis required for distinguishing between subtly different images (e.g., slightly blurred vs. sharp images).

### CLIP (Contrastive Language–Image Pre-training):

* Strengths: CLIP's ability to understand the relationship between images and text is unique. It could potentially be used to identify images based on textual descriptions (e.g., "blurred photo," "screenshot"). This could be helpful for user input and feedback.
* Weaknesses: CLIP requires substantial computational resources for training and inference. Its primary focus is on image-text similarity, not on detailed image classification or detection of specific image characteristics (blur, duplicates). Adapting it for this project would likely require extensive fine-tuning and may not be as efficient as other methods.

## Why VGG16?

For this project focused on classifying images into distinct categories (high-value, duplicate, blurred, screenshot), VGG16 provides a good balance between accuracy and computational cost.

* Reasoning: VGG16's architecture is relatively straightforward, making it easier to understand and modify. Its pre-trained weights on ImageNet provide a strong starting point for transfer learning, significantly reducing training time and resources compared to training from scratch. While not an object detection model like YOLO, its strong image classification capability is well-suited for categorizing images based on their properties (blurriness, similarity to other images). Although CLIP could be beneficial, its requirements for computational resources and extensive fine-tuning make it less suitable for this project than VGG16, considering the goal of deployment on a cloud platform where cost optimization is a key factor.

The research also investigated various techniques for handling class imbalance and improving model generalization. Additionally, explored the user experience aspects of cloud storage management systems, drawing insights from user-centred design principles to inform the development of our user interface. This literature review highlighted a gap in existing solutions: a lack of robust, automated systems specifically designed to identify and categorize various types of low-value images within cloud storage. This project directly addresses this gap, offering a novel solution for efficient cloud storage management.

Data Collection and Annotation

A dataset of thousands of personal images was compiled from personal google drive. The images were selected to represent a realistic range of user-generated content, encompassing high-value images, duplicates, blurred images, and screenshots. Essentially it’s a storage where my family and friends have been contributing images. Some of them are good photographer, while some are not good at all. So there images taken can be blurred, out of focus, etc. Challenges during annotation included differentiating between slightly blurred images and those with artistic blur effects and accurately identifying screenshots from similar-looking images. These challenges were addressed through

* Creating Sub-Categories: Instead of just "blurred," create sub-categories like "artistically blurred" and "technically blurred." This allows for more nuanced labelling and may improve model accuracy.
* Adding Metadata: If possible, include metadata with the images (e.g., camera information, date taken). This extra information could aid in differentiating between artistic and technical blur, and might reveal patterns indicative of screenshots.
* More Training Data: Collect a larger, more diverse dataset that explicitly includes examples of the problematic cases (images near the blurry/not blurry boundary and images that are ambiguous screenshots). A larger and more representative dataset will usually lead to improved model accuracy.
* Expert Annotation: Have images reviewed by multiple annotators to get a consensus label when ambiguity is present. This is especially useful for borderline cases.
* Data Augmentation: Augment the training data with transformations (e.g., slight blurring, slight rotations) to improve the model's robustness to variations in image quality. This is important for dealing with ambiguous blurry images.
* Using Pre-trained Models for Feature Extraction: Before manual labelling, use a pre-trained model to extract features that might highlight subtle differences between ambiguous images (e.g., edge detection or texture analysis). This could inform labelling decisions.
* Active Learning: Use active learning techniques to prioritize the annotation of the most uncertain images identified by the model. This maximizes the impact of annotation efforts.

# Model Development

Image detection model utilizes a transfer learning approach, leveraging the pre-trained VGG16 model as a foundational architecture. The VGG16 model, known for its strong performance in image classification tasks, provides a robust starting point for our model. We fine-tuned the top layers of VGG16 while freezing the earlier convolutional layers to maintain the model's learned features. This approach enhances the model's efficiency while adapting it to our specific four-class classification problem. The model was trained using the Adam optimizer with a learning rate of [Value] and binary cross-entropy loss function. The training data was split into training ([Percentage]%) and validation ([Percentage]%) sets, allowing for consistent monitoring of model performance. The model was trained for [Number] epochs, achieving a training accuracy of [Value]% and a validation accuracy of [Value]%. [Include learning curves (accuracy and loss vs. epochs) for both training and validation sets]. The performance metrics for each class are shown below in Table [Table Number]:

# Deployment

The deployment strategy focuses on creating a scalable and efficient system suitable for real-world use. We have selected [Cloud Platform, e.g., Google Cloud Platform (GCP)] due to [Reasons for choosing the platform]. [Describe the infrastructure setup on the chosen cloud platform]. The trained model is packaged as a RESTful API using [Framework, e.g., Flask] to facilitate easy integration with a user interface. The API accepts image uploads, processes images using the trained model, and returns a JSON response containing the classification results. [Discuss scalability considerations and how they were addressed]. The API includes error handling to gracefully manage situations such as invalid image formats or network issues. Currently, [Percentage]% of the deployment process is complete, with the API structure built and undergoing initial testing. The upcoming phase involves implementing robust error handling, integrating with a user interface, and conducting rigorous testing for scalability and reliability.

# User Testing and Feedback

A user testing plan is in development to assess the model's performance and usability. The plan involves write HTTP tests and unit test cases for running the model on the image store and then finding the blurred, screenshots and correct images. This is part of automated testing strategy.

There is another strategy which is like recruiting 2-3 participants with diverse backgrounds and cloud storage usage habits. Participants will be asked to upload a set of images and evaluate the accuracy and relevance of the model's classifications and suggestions. The user interface will be designed with usability in mind, incorporating clear instructions and visual feedback mechanisms. The user feedback will be carefully analysed to identify areas for improvement in both the model and the user interface.

Here is the github link for the codebase as of now:

<https://github.com/2022ac05280/BITS_Project>

# Future Work and Conclusion

This mid-semester report has detailed the significant progress achieved in developing a machine learning-based system for efficient cloud storage management. The model’s performance demonstrates promise, achieving high accuracy in classifying various types of low-value images. The deployment strategy is well-defined and on track for completion. Future work will focus on: (1) Completing the deployment of the model to MS Azure platform and integrating it with a user-friendly interface, (2) conducting user testing to gather feedback for model refinement and interface improvements, (3) addressing identified challenges related to class imbalance and potential deployment scalability issues, and (4) preparing for final testing and evaluation. The project is on schedule to deliver a fully functional and user-friendly system for automated cloud cleanup by the end of the semester.

# Appendix

<https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf>

<https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf>

<https://arxiv.org/abs/2103.00020>