Computer Vision-based Product Recommender

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Abstract - **Most E-commerce search engines are still largely dependent on keyword matching and the user's knowledge base to find the product that fits most into the customer's requirement. This is inefficient in the sense that the description (keywords used) can vary a lot from the buyer's side to the seller's side. In this paper, we propose adding another layer to the search criteria. This smarter search engine would basically capture an image as the input and try to classify the image into a product description. This can also make searching for a product much faster and easier. Therefore, there is room for improvement in the search process and for making the customer experience smoother. The implementation proposed is a mobile application with a fast and interactive UI that classifies an image into its corresponding product class, using machine learning, which is then used as a search query in Amazon to list the products. To build such an application that has machine learning at its core we need to incorporate a development process/methodology that is able to have a focus on the aspects of ML domain that make it fundamentally different from other software application domains.**

Index Terms - Application Programming Interface (API), Artificial Intelligence (AI), Computer Vision & Image Processing, Convolutional Neural Networks (CNN), Machine Learning (ML), Mobile application, Software Development Process.

Introduction

The E-commerce system is fast-evolving and online shopping is rapidly becoming an unavoidable part of our daily lives. The latest challenge that online shoppers face is the sheer amount of digital information. This explosive growth creates an information overload, which in turn, inhibits timely access to items of interest on the Internet. Herein lies the need for a recommendation system. Almost every E-commerce website has its own implementation of a recommendation system based on available data such as recent searches, prior purchases, etc. The aim of such a system is to give the customer an efficient and more personalized experience. However, most recommendation systems are text-based and usually rely on keyword matching systems and the user's knowledge base. Moreover, the text-based description of a product can vary a lot from the buyer's side to the seller's side. With the rapid development in computer vision owing to the improvements made by neural networks these recent years, we can now make a shift from traditional word-based searching methods to searching methods involving visual similarity [5].

Similar to the way machine learning has impacted how recommendation systems are being built, advances in machine learning have also stimulated widespread interest in incorporating AI capabilities into software and services in other domains. To be able to effectively build such applications new development processes must be employed as traditional development processes cannot be used owing to the many differences we encounter upon incorporating machine learning into an application. These differences arise due to 1) building, monitoring and versioning being more complex than other kinds of software engineering, 2) the modularizing of internal AI components being difficult when incorporating multiple AI techniques for a single task. So to build ML based applications in a smooth way the right choice of a software development process becomes a task of utmost importance. In this paper we also explore how we incorporated existing software processes by modifying them to suit the development of our application based on the literature available for software engineering methodologies for AI.

Our product is a mobile application with a fast and interactive UI that classifies an image into its corresponding product class, using machine learning, which is then used as a search query in Amazon to list the products. We achieve this computer vision task of mapping the image of a product to its product class by using MobileNetV2 as the architecture for the machine learning classification model. We run the model on device and hence the computational resources of the device becomes an important consideration. MobileNetV2 is able to retain similar accuracies as larger models while minimizing the number of operations making it the apt choice.

In machine learning the performance of a model is strongly tied to the kind of data it is trained on. Hence it is always good to have as much data as possible. This makes data collection both during the initial stages and user feedback stages very important. Our application is also built with making the data collection during the user feedback stage an important focus. We collect the image captured and the user-suggested product class as feedback from the user when our application makes a wrong recommendation. We discuss also in our paper how we may use this data to retrain our model to improve its performance.

Literature Review

- Saleema Amershi et al. [1] gives a description of a nine-stage workflow for integrating machine learning into application and platform development. A set of best software engineering practices for building applications and platforms relying on machine learning is also described here. We have used the practices described here while implementing our own ML-based application.
- Luyang Chen et al. [2] presents a smart search engine for online shopping. An implementation of the image search functionality is discussed.
- Mark Sandler et al. [3] describes a new mobile architecture MobileNetV2 that improves the performance of mobile models on multiple tasks and benchmarks. MobileNetV1 introduced the concept of depthwise separable convolutions which reduced the inference time by reducing the total number of multiply-add (M-add) operations by a factor of $\sim k^2$ (where k is the convolution filter size). In most cases, k=3 and hence we get a speedup of 8-9 times with little reduction in accuracy of the model. MobileNetV2 introduces the concept of residual blocks and linear activations on top of depthwise separable convolution. Residual blocks allow the free flow of gradients throughout the model which allows us to train extremely deep models with high classification accuracy. A linear activation is necessary before the residual operation in order to avoid loss of information before projecting to a lower dimensional space (ReLU activation cannot be used; it is always zero for negative inputs).
- Daniel Kang et al. [4] describes the abstraction of model assertions for monitoring and continuously improving ML models and how such assertions can integrate into the ML development, and its implementation. Model assertions and uncertainty estimates are used in every step of the ML pipeline - from collecting data, labelling it, training the model and during deployment/inference. The authors propose a method to utilize active learning to improve the performance of the model. The model assertions help identify examples which can be used for active learning. The authors also propose a type of model assertion called a consistency assertion - which is used to automatically generate weakly labelled data to further train the model to improve its performance. The model assertion abstraction defined here is applicable to any general ML system, and is not restricted to our use-case of recommending products from input images.
- Sean Bell et al. [5] talks about the visual similarity between objects and the impact it has on the product design. They present a crowdsourced pipeline to match in-situ images and their corresponding product images. They also illustrate how to use this data, using convolutional neural networks, in image search applications like finding a product and finding visually similar products across categories. Our application also seeks to identify product classes from captured images using CNN.
- Tom Diethe et al. [6] describes a reference architecture for self-maintaining systems that can learn continually, as data arrives. In environments where there is a need to update / train our model with new data, we need architectures that adapt to shifting data distributions, cope with outliers and retrain when necessary. This represents continual AutoML or Automatically Adaptive Machine Learning. The conclusions drawn in [6] are useful for the development of the feedback mechanism in our application.

Main Text

Scope Of The Work:

The implementation chosen for our product is a mobile application for the very simple reason that it will be the most convenient for the user. The cross-platform mobile application will be able to classify and recommend products based on the image captured by the user. From the image data, the application determines what product is to be searched for. Upon successfully processing the image and producing the text-based classification of the image, the app is redirected to a list of recommended products on Amazon using the Google CustomSearch API. If the recommendation was wrong or only partially correct, then, a mechanism is available to collect the feedback which is then stored in firebase to refine the machine learning model at a later time.

The application UI will be developed using flutter as it is a free and open source platform independent framework. The underlying image classification unit will use MobileNetV2 for processing the image and producing the recommendation. For some images, it is not enough to just classify it. For example, properly searching for a book requires identifying the title of the book also. In these cases, an OCR text recognition algorithm can also be applied to improve our app. This functionality is not currently included in the design of the app as of now. After the specified requirements have been met, this functionality may be included if possible.

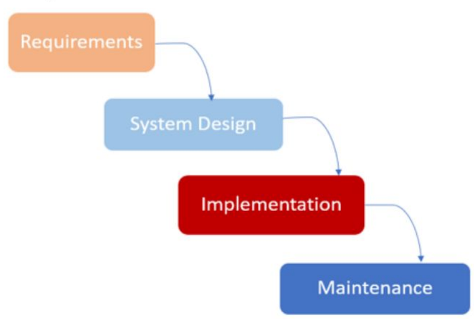
The main deliverable of this project is a cross-platform mobile app that would perform the following tasks:

- Captures the image and feeds it to the image processing unit.
- The image classifier uses the tensorflow model run on the device to process the image and output the text-based classification of the captured image.

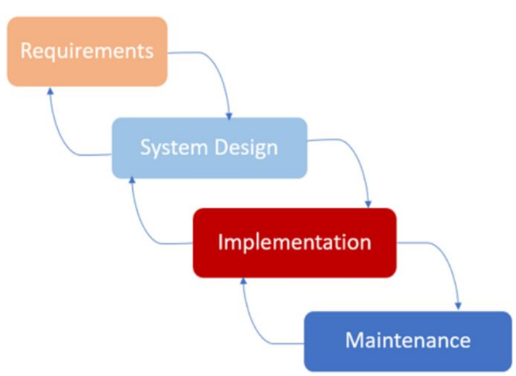
- Feedback mechanism which collects the feedback and stores it which can then be used to improve/refine the model at a later stage.

Software Engineering Applications:

The software development life cycle proposed is the waterfall model with backflow. This improves upon the traditional waterfall model by incorporating a backflow and provision for getting customer feedback. We took influence from the agile model wherein, at the end of every sprint (dev cycle) the product owner will validate the delivery and provide feedback. Collecting feedback from the product owner at frequent intervals throughout the product development cycle will enable us to ensure that whatever is being delivered is in accordance with the client's requirements. This will also help in reducing the amount of wasted effort due to gaps in requirements gathering. However, our software has well-understood, unambiguous and stable requirements. For such a scenario, the agile methodology is not apt. However, feedback from the client is a necessary step in the development cycle of any software. For this reason, a backflow is incorporated into the waterfall model for smooth development.



Waterfall Model



Waterfall Model with Backflow

The feedback unit of our implementation of the mobile app lies in the maintenance part of the waterfall model specified above. The feedback unit seeks to apply the concepts of continual learning [6] to gather data and use it to refine the model. When the image processing is done, the application will search the recommended product on Amazon and return the relevant results. If the recommendation was wrong or only partially correct, a mechanism is implemented to collect the user-suggested class. Then, in keeping with the requirements specified, the feedback (the captured image and the user-suggested class) is uploaded to the image database.

However this system runs the risk of using invalid/wrong data to train the image classifier. For example, a user can suggest that the picture of a table is a chair. This feedback data should also undergo some checks before being added to the training data. In machine learning, the performance of the model is very strongly tied to the kind of data it is trained on. So, to build ML based applications which continuously learn, the right choice of a software development process becomes a task of utmost importance.

This is how existing software processes, related to machine learning and artificial intelligence [1], have been incorporated by modifying them to suit the development of our application.

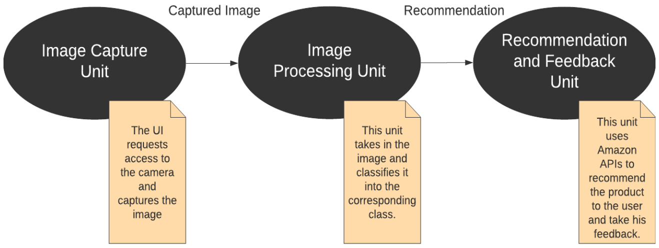
Model:

Model Driven Design (MDD) is described as the separation of business decisions from the software oriented decisions by making use of the interoperability of formal models. Basically, we use *models* (may be conceptual, logical, physical, etc) to describe the functionality of the *solution,* independent of any software-oriented decisions.

We will use a visual (conceptual) model to describe the working and operations performed by the computer vision-based product recommender. This model is described according to the requirements specification and does not depend on any implementation details. This model is later used to implement the proposed mobile application.

The mobile app itself can be divided into three main divisions:

- Image Capture: This unit deals with capturing the image and feeding it as input to the image processing unit. This requires access to the mobile camera so that the image can be captured.
- Image Processing Unit: The image processing unit deals with computing on the image and providing text based keywords for the closest matching classifications.
- Recommendation and Feedback Unit: This classification acts as a keyword for an API-based search on Amazon (or any other shopping website). On completion of this recommendation, user's feedback will be requested which will then be used to improve our model.



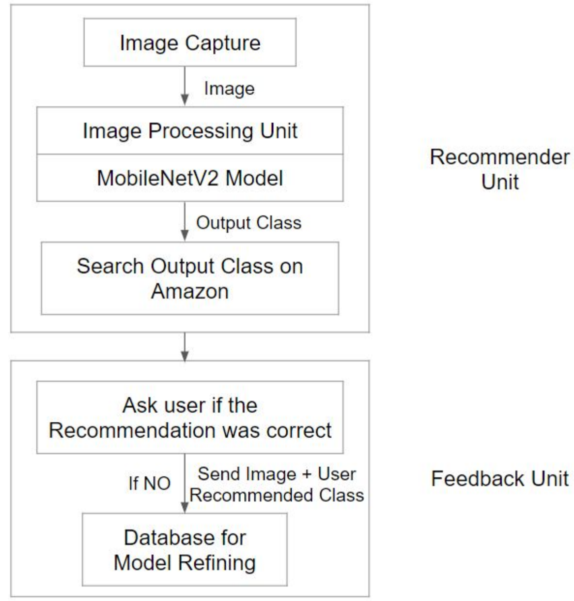
This model is independent of the programming language that will eventually be used for the implementation of the mobile application. This conceptual model describes the sequence of the operations performed in the application.

WORKING:

The computer vision-based product recommender does the following tasks,

- It uses the camera of the user's mobile device (after asking user's permission of course) in order to get the image needed.
- It then captures the image when the user taps on the capture button and the user is then redirected to a confirmation screen where the user can either continue with the currently captured image or go back to the camera to retake the image.
- Once the user is satisfied with the captured image, it is then passed as input to the image classifier.
- The image classifier makes use of the MobileNetV2 architecture trained over the ImageNet dataset as the ML model. With a softmax operation at the final output layer in the ML model we get a probability distribution for the product class over the 1000 supported classes of the ImageNet dataset.
- We then return the output classes with the highest probabilities as a list of possible product classes.
- The user can go through this list of classifications and click on the closest match. This triggers the opening of a webview within the application and redirects the user to the Amazon product list view.
- When the user returns to our application, an alert immediately pops up and asks the user if the experience was satisfactory and the recommendation was correct. If the user says that the recommendation is correct, then the app redirects to the home screen.
- If the user says that the recommendation was wrong, then he is directed to another screen with a text field which allows the user to enter a suggestion. This suggestion along with the image and the recommendation our app provided, is stored in a database maintained in firebase.
- Then, after the feedback is collected, the user is then redirected to the home screen.

A flowchart showcasing the major components of the computer vision-based product recommendation system is shown below:



PLATFORMS AND LANGUAGES USED:

The computer vision-based product recommender requires the following open-source/readily-available platforms/language support.

- Operating System : Android 8+ / IOS
- Frontend: Flutter/ Dart constitutes the codebase and SDK used to develop the application.
- Backend: Firebase for the efficient storage and retrieval of user feedback data.
- Image Processing Unit: Uses MobileNetV2 architecture [3] for the ML model with python and tensorflow.

Why flutter?

Flutter is a free and open source mobile UI framework from Google that provides a fast and expressive way for developers to build native apps on both IOS and Android. It facilitates fast development, expressive and flexible UI and very high performance apps with minimal effort on the developer's part. Because it is platform independent, it can be used by both android and IOS developers with the same codebase and it automatically gets converted to the corresponding codebase: swift or objective C on iOS and kotlin or java on Android. This eases the effort for the developer during the initial development phase by requiring him to maintain only one codebase for both platforms. This also decreases the time and thus, the cost of updates and maintenance of the app. Moreover, flutter is completely free and open source, which allows for the incorporation of many packages and features that the open source community has developed. The framework also gets regular updates from

Google's flutter team making it one of the most popular frameworks for app development. For these reasons, flutter has been chosen as the implementation framework for the computer vision-based product recommender.

Why MobileNetV2?

In the implementation proposed, the image processing unit is run on the device and hence neural networks that require high computational resources cannot be used. MobileNetV2 pushes the state of the art techniques for mobile tailored computer vision models, by significantly decreasing the number of operations and memory needed while retaining the same accuracy, making it an appropriate choice for the machine learning architecture used.

Contributions To Software Engineering:

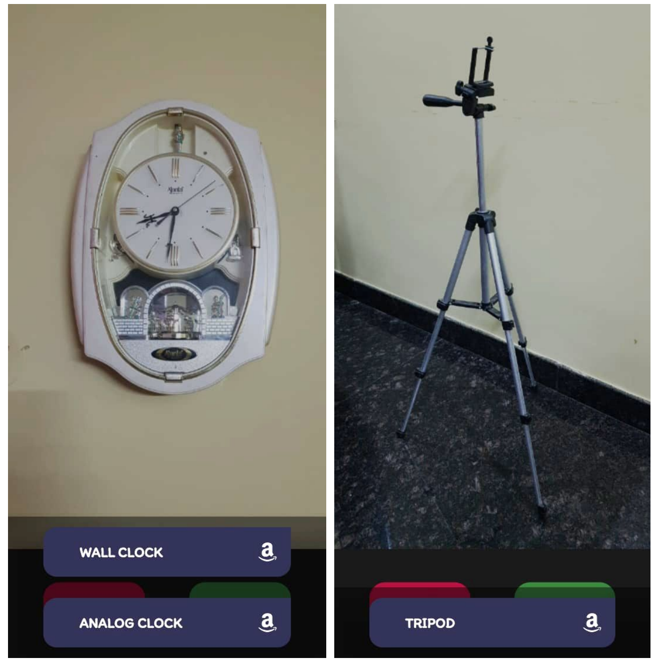
The computer vision-based product recommender is a mobile application where the various stages of the machine learning workflow can be clearly identified. One of the reasons for this is because in our application data collection during the user feedback stage is a major focus. After sufficient data is collected in the feedback database maintained in firebase, we can also look into how it can be best used to improve the ML model. This phase would involve verifying the data collected using appropriate content filters and model retraining, testing and redeployment. Because of these reasons our application is a good example of a general ML based application. Examining how our application is structured and built can help readers better understand some of the stages involved in a ML workflow and help them build other simple ML based applications.

Results:

The image classifier model makes its prediction for the product class using a pre-trained ML model available at: "https://www.tensorflow.org/lite/guide/hosted_models". We chose to use the floating point Mobilenet_V2_1.0_224 model from the above link which has been trained over the ImageNet dataset and reports a Top-1 accuracy of 71.8% and a Top-5 accuracy of 90.6% over the same dataset. This model is both lightweight taking up only 13.3 MB of space and runs quickly on-device with a good classification accuracy which suits our application use case.

However, since the pre-trained model was trained over the standard ImageNet dataset, it has several classes that are not related to consumer goods. We later plan to train our classifier model on a subset of ImageNet that has more relevant classes. This will improve the performance.of our product recommender as the model will learn more relevant features that will enable it to better distinguish between different consumer products without having to learn about some of the highly varied classes of ImageNet that are irrelevant to consumer product recommendation.

Our proposed implementation is available at *"https://github.com/sangzzz/Image-based-Product-Recommender"*. Screenshots showcasing some working examples of product class recommendations made by our application are shown below:



Conclusion and Future Work

The cross-platform mobile application for the computer vision-based product recommender has successfully been implemented using Flutter/Dart for the user interface and MobileNetV2 architecture for the image classifier model.

There is scope for improvement in the computer vision-based product recommender implementation. For some images, it is not enough to classify it into its corresponding class, which may be too large at times. For example, if our app returns the classification *book*, that doesn't make any sense to an online shopper. It should return the title of the book if the recommendation is to be of any use. In such cases, an OCR text recognition algorithm running simultaneously can also be applied to improve our app. This functionality is not currently included in the design of the app as of now.

The recommendation is shown to the user using Google's CustomSearch API. The free tier of this API allows for only 100 API calls per day and anything more will require a monetary compensation. This is a student undertaking and as such does not have the funds nor the resources to properly utilize this API. Therefore, scaling the application is as of now, not feasible.

Another region where the app can be improved is the implementation of the feedback mechanism. Most users would not want to provide feedback and those that do will probably not want to type the recommendation out. So, providing a text field that would auto suggest products, from a product database, to the user will make the feedback mechanism much smoother. Also, a proper filter on the feedbacks that get stored onto the app's cloud maintained database is necessary to avoid the unnecessary wastage of resources. Moreover, in the current implementation we have allowed for the user's feedback to be stored in firebase to later be used to improve the model. However, this process has to be done manually. Automating this process is a must for scaling the application.

To improve the image search further, we can use ideas mentioned in [2] and [5] where we maintain a database of feature vectors of product images on Amazon. In the case where the model predictions are incorrect or the input image does not belong to one of the supported product classes, we can employ this method. Here, we obtain the feature vector for the user query and rank the feature vectors in our database using a similarity metric. This is recommended to the user in such failure cases. In [4], they introduce the concept of model assertions to identify runtime errors such as this. We can also use Bayesian uncertainty estimates of the neural network output to determine when the model is not confident about its prediction. In such cases, we can trigger the implementations mentioned in [2] and [5].

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