MOOCs RECOMMENDER BASED ON USER PREFERENCE, LEARNING STYLES AND FORUM ACTIVITY

Project ID: 19-089

Project Proposal Report

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DECLARATION

We declare that this is our own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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ABSTRACT

Massive Open Online Courses also known as MOOCs for short has becoming a popular mean of learning in a wide variety of subject scopes. But, one of the major problems with MOOCs is that the completion rate tends to be low. Interestingly, one of the reasons behind the low completion rate can be identified as the mismatch between a learner's learning style and delivery style (video style) of a MOOC, as identified in a research conducted by a group of undergraduates of Sri Lanka Institute of Information Technology in 2018, on which this very research is going to be based on. While the aforementioned research did pave the way to a tool called MOOCRec which will be referred to as MOOCRec V1, through this research we aim to mitigate the draw backs MOOCRec V1 has, while switching to a more distributed and parallel computing-based architecture and increase the number of different video styles the tool is able to identify. Furthermore, we plan to integrate a more elegant way of identifying a learner's learning style and take the activity in MOOC related forums and online discussion spaces into account when recommending a MOOC.

In this research, the main goal is to develop a more straightforward implementation to identify which video production styles of MOOCs a user prefers and use sentiments and opinions on forums to suggest more relevant and suitable MOOCs to users. Also, this research will look into the possibility of classifying videos parallelly, by utilizing a distributed, containerized compute instances to boost the efficiency of image processing and classification. Furthermore, another goal of this research is to explore how a wide range of complex video production styles can be identified with higher precision and a very low rate of false-positives.

To summarize, this research will extend and improve on an existing tool to explore how a more refined and elegant solution can be introduced to recommending MOOCs that suit the user to further uplift the benefits that one can gain by following a MOOC that best fits him or her.

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LIST OF ABBREVATIONS

MOOC	Massive Open Online Course
SIMD	Single Instruction Multiple Data-stream
ILS	Index of Learning Styles
CNN	Convolutional Neural Network
VM	Virtual Machine
NLP	Natural Language Processing
ML	Machine Learning
VGG	Visual Geometry Group
FSLSM	Felder Silverman Learning Style Model

Table 1: List of Abbreviation

1. INTRODUCTION

1.1 Background

Massive Open Online Courses also known as MOOCs for short, has become a popular medium for learners of different fields to learn new things but the completion rate of MOOCs happen to be low. It is identified that one of the main reasons behind this is the mismatch between how a person learn and how the MOOC is delivered in terms of the video style. Several learning models such as Felder-Silverman Learning Model and Kolb Learning Model indicate a set of different learning styles that a person might have [1]. As established in the Abstract, MOOCRec V1 was able to identify the learning style(s) of a person using a albeit lengthy questioner. By basing our start on MOOCRec V1, we plan to mitigate any drawbacks, issues that MOOCRec V1 has while extending its functionality and scope further along with an architectural change to support parallel processing when classifying MOOCs to make the process efficient and fast. Also, with more and more users joining forums and online discussion spaces, we will also take the activity on such spaces into account as a metric for recommending a MOOC.

To elaborate further, we are planning to extend MOOCRec V1 into MOOCRec V2 in following aspects.

1. A different and elegant way to identify the learning style(s) of a person.
2. More video styles in a different variety of fields.
3. Parallel MOOC classification.
4. Discussion forum analysis for users' sentiments about a particular course.

To summarize, our main goal is to better identify what sort of a learning style(s) a user has in a seamless way, and recommend MOOCs from a wider variety of learning material types and technical fields while taking user's sentiments in online discussion spaces to further strengthen the recommendations while architecting infrastructure and processes to be able to classify MOOCs faster and more accurately even with an increased number of different video styles in different technical fields, thus creating MOOCRec V2.

1.2 Literature Review and Survey

- Parallel MOOC classification.

  Parallel Processing for Video Classification Using Distributed Service Workers Given the popularity of MOOCs and the increasing number of MOOC providers as well as the number of new MOOCs by the day, our system will be tasked with extracting and analyzing thousands of videos. Provided that each video will be broken down to individual frames and then classified on a per-frame basis, the number of frames that must be processed is enormous and the most immediate bottleneck for this whole process is CPU performance.

  In general, parallel processing can be classified into 4 categories [2].

  - Single Instruction Single Data Stream **(SISD)**
  - Multiple Instruction Single Data Stream **(MISD)**
  - Single Instruction Multiple Data Stream **(SIMD)**
  - Multiple Instruction Multiple Data Stream **(MIMD)**

  Out of above approaches to parallel processing, given that we have a large amount of image frames that belong to different videos and the fact that we only train one image classifier to identify a range of video styles, the ideal approach is to use SIMD where we have multiple nodes, each running the same classifier(thus Single Instruction) while each node is fed different image data(thus Multiple Data stream). While this seem ideal in theory, the major concern involving this approach is analyzing the output given for each frame analyzed.

  This requires a sufficiently capable orchestrator that keeps track of which frame belong to which video and what output was given by a classifier node for that frame. Also, the orchestrator must be aware of how many frames where extracted from a video file and to which MOOC the said video file belongs. This overall approach can be described as a MapReduce solution [3]. For such a data-intensive task, Apache Hadoop seems to be ideal but given that the base of it is written in Java and the questionable compatibility of Python based Machine Learning classifiers with Hadoop eco-system, the need to identify a more customizable solution is abundantly clear.

  With the advancement of virtualization of operating systems and the rise of Docker which paved the way to running applications within containers which was faster than a VM and Kubernetes which made running a cluster of such Docker Containers [4], the performance gain that can be achieved by utilizing Docker for running multiple instances of an image classifier appears ideal after much research. To summarize, by analyzing existing literature on both Parallel Computing as well as Virtualization, feeding multiple streams of data to multiple instances of a classifier running on Docker containers seems ideal for parallelly classifying thousands of image frames, efficiently while utilizing all available hardware resources, while also making sure the overall system is highly scalable due to its independent and distributed nature.

- Analyze and classify newer and complex types of MOOC video styles

MOOC resources include multiple modalities such as lecture videos, audio transcriptions, slides, textbooks, forum discussions and clickstream log data. Among them, lecture video is arguably the central and omnipresent component for knowledge transfer, to which other data modalities support. Thus, we focus on designing a method that can organize video resources to dynamically fit different learners. There are countless MOOC courses in the Internet with countless videos associated with them. People have emphasis on retrieving those videos with specific category and it is infeasible for user to go through tremendous number of videos and find the video of interest. The diverse learning styles and backgrounds suggest that leaners may need nonlinear learning paths to suit their needs during lecture watching [21]. These may include searching, skipping and reviewing. These activities are commonly found in MOOCs based on the analysis of Kim et al.[26] on million log events. Separating information in a video requires segmenting and annotating videos in high, structural granularity.

Generally, the types of content in MOOC videos include: talking head, slide, coding, animations, writing (khan academy) etc. In production of some MOOC videos, there are lot of transitions between visual views, e.g.: switching from a talking head to a slide or switching from a slide to an animation. Here, we propose an Automatic Visual Transition Boundary Detection method to partition MOOC videos into segments according to the video production style.

Another goal is to synthesize photo-realistic talking heads of high quality that show picture-perfect appearance and realistic head movements with good lip-sound synchronization. Speech is usually accompanied by head movements, facial expressions, and gestures, applied by the speaker underlining the meaning of the spoken words according to [26]. Understanding quantitatively the correlations between head movements and spoken words is important for synthesizing photo-realistic talking heads. Talking heads appear much more engaging when they exhibit realistic motion patterns. Nonverbal components in face-to-face communication have been studied extensively, mainly by psychologists. Such studies typically link head and facial movements or gestures qualitatively to parts of the spoken words. Many of the more prominent movements are clearly related to the content of spoken text or to the situation at hand. For example, much of the body language in conversations is used to facilitate turn taking. Other movements are applied to emphasize a point of view. Some movements serve basic biological needs, such as blinking to wet the eyes. Moreover, people always tend to move slightly to relax some muscles while others contract. Being completely still is unnatural for humans and requires considerable concentration.

Detecting whether a video is an animation is a crucial task because distinguishing between ‘animation’ and ‘photographic image’ has proved difficult because of their large intra-class variation [23]. We call images animations if they do not contain any photographic material. Some distinguishing features of animations are:

- Few, Simple and Strong colors: The abstraction in transforming a real-world scene into the animations leads to a reduction of colors and exaggeration in saturation.
- Patches of uniform color: Textures are often simplified to uniform color.
- Strong black edges: The large patches of uniform color are often surrounded by strong black edges.
- Text: Educational cartoons, charts, etc. often contains large text that is typically horizontal and not distorted by a perspective transformation. Moreover, the fonts are chosen to be readable and the colors to give good contrast [23].

- Online forum thread discussion analysis to aid in recommending MOOCs and Forums for a given MOOC

Users who learn through peer-to-peer interactions need to find MOOCs which have an active community, so that the user too will be able to participate in it. Previous research has shown that discussions have a positive impact on learning effectiveness [5].

The research paper [6] describes an intelligent web crawler called ‘iRobot’ which can identify web forums with minimal initial data and figure out how to traverse the forum. Though the system in that paper does not find content relevant to a specific MOOC or topic it has a major advantage in the fact that it can identify crawling paths through forums by itself, therefore it will be able to cover a larger number of links.

The web crawler described in [7] had aimed at gathering data using regular expressions which is a template-based processing method. As a result, the information acquired is structured which makes it easier to process them later, but the disadvantage to this method is that the regular expressions must be explicitly written for the data that the system is attempting to collect. So, the system could miss out on potential information if it is not designed to do so.

A general sentiment analyzing model which was trained using 300,000 twitter posts was presented in [8]. The results of the research paper show that the model was able to identify user sentiments with decent accuracy. A multinomial Naïve Bayes classifier had been chosen to use the model data to make the classifications.

Sentiment analysis has been done in a much different approach in [9] by B. Pang et al. Before the data is used to trained or classified, the system proposed compresses and removes any unnecessary subject domain text while retaining polarity information. Basically, it compresses the data before processing, as a result the performance was increased. In addition to that, the process increases the accuracy because the removal of unnecessary data makes the data cleaner and has a lower chance of being misidentified by the Naïve Bayes classifier.

Though previous research has shown positive results in the field of web crawling and sentiment analysis, they were not regarding the context of discussion forums relating to MOOCs. Therefore, research is needed to determine whether information (ratings derived from sentiments, other forum thread metadata) contained within forums can be used to improve MOOC recommendations.

- Identifying user's preferred learning style(s) and recommending suitable MOOCs.

While MOOCs are ever so popular among the mass crowds, the completion rate of MOOCs has been found out to be low by many researches done on the engagement of consumers with MOOCs over the duration of courses [10]. Furthermore, pioneering researches such as Felder-Silverman Learning Style Model [11] has highlighted the importance of acknowledging that an individual can inherit a learning style or few that he or she will be more inclined towards and dimensions that an individual can fall into, such as Active or Reflective, Visual or Verbal, Sensory or Intuitive, Sequential or Global. This is another factor that cannot be overseen when recommending MOOCs to an individual since a certain type of MOOCs can appeal to a certain dimension.

Upon further investigation, it was realized that Index of Learning Styles (ILS) questioner [11] [12] exists to determine the dimension that an individual fit into, from the aforementioned set of learner dimensions [13], devised by Richard M. Felder and Barbara A. Soloman [13]. Another interesting fact about this questioner is that it is a lengthy questioner that consists 44 multiple choice questions [14] [13] . However, based on a survey conducted the overwhelming majority of the participants appeared discouraged to fill 44 questions [Figure 11]. It is the conclusion of the aforementioned survey that led us to research a better solution to identify the learning-dimension/style of an individual.

Evidently, there is a research that is based on the engagement of an individual with a learning activity and the facial expressions shown during the said engagement [15]. Throughout the research it is discussed how a certain set of facial expressions where shown during a high level of engagement with a learning task while another set of facial expressions were associated with low level of engagement. By using this range of facial expressions, the level of engagement can be predicted [15]. With more investigation, it is found that a two-dimensional mapping which is prepared considering learning style characteristics and MOOCs characteristics exist [12] in order to help decide, which learning material type suits which learning style., i.e. if a MOOC video contains a given percentage of a talking head video style, then the MOOC video is more likely suitable for an intuitive, verbal and global learner [12].

Therefore, based on above facts, it was concluded the based on the facial expressions shown by an individual, we can identify how engaged that individual is, with the given task. Furthermore, by providing an interactive, yet concise session that contains MOOC related videos that belong to different learning-dimensions by considering the aforementioned learning material type to learning style mapping, we can effectively identify to which learning-dimension that an individual fall into by identifying the learning-dimension of the MOOC video during which, the individual showed the highest engagement. However, for capturing the facial expressions of an individual, a service has to capture the video feed, ideally from a webcam, which tends to raise a privacy concern. To further investigate how potential consumers might feel about this, another survey was conducted among undergraduates of SLIIT to identify how they feel about letting a service access the camera feed even for a small amount of time. Interestingly, 80% of the participants permitted providing access to the webcam specifically for an e-learning platform, for a short, one-time-only interactive session to help the service identify their learning-dimension [Figure 12].

1.3 Research Gap

Even though MOOCRec V1 has introduced a set of key features that were not present in any other tool a year ago, through literature review we identified a set of key areas that can be improved or extended along with a new feature that is not present in MOOCRec V1. Also, during the phase of literature review, there were no other tools that matched the feature set offered by MOOCRec V1; which led us to compare MOOCRec V1 and our proposed solution, which is referred to as MOOCRec V2.

In areas such as processing, using resources optimally is an area that MOOCRec V1 has not covered. Also, it was clear that newer video styles can be introduced to broaden the number of recommendations that can be provided across a range of learning-dimensions. Furthermore, how the learning-dimension/style of a user is identified is another aspect that could be improved. Lastly, by adding forum analysis to strengthen how MOOCs are recommended to users, we will be improving, and extending the user-experience, performance and functionality in our proposed solution, MOOCRec V2.

As a result, the following feature comparison can be highlighted.

Features	Class Central	My MOOC	MOOCRec	Proposed Solution MOOCRec V2
Directly identify users' preferred MOOC learning material type(s)	✗	✗	✗ *based on learner style*	✓
Video Production Style of MOOC videos	✗	✗	✓	✓
Complex and mixed video production styles of MOOC videos	✗	✗	✗	✓
Identify the spoken language of the presenter in a MOOC video	✗	✗	✗	✓
Search filter based on specific keywords / topics	✗	✗	✓	✓
User profile and dashboard	✓	✓	✓	✓
Online discussion forums analysis and extraction of sentiments of forum posts for better MOOC recommendations	✗	✗	✗	✓

Table 2: Feature comparison between existing products vs proposed solution

1.4 Existing Products

There are many tools in the internet that let the user search MOOCs based on a range of categories and filters and some even recommend more MOOCs based on the history of a user. Apart from these similar tools, MOOCRec V1 is the only tool that takes a person's learning style into account when recommending a MOOC.

- MOOCRec (referred to as MOOCRec V1 for differentiating our proposed solution, MOOCRec v2)

Figure 1: MOOCRec

A MOOC recommender that identifies the learning style of a user through a lengthy questioner. It indexes MOOCs from Coursera, Edx and Futurelearn. MOOCRec also has user profiling.

- Class Central

Figure 2: Class Central

Class Central is one of the most popular MOOC search engines that also makes recommendations based on the fields of studies and institutions that a user would prefer. But Class Central does not recommend MOOCs based on the individual learning style of a person.

- My MOOC

Figure 3: My MOOC

Another popular MOOC search engine that focus facilitating users to rate MOOCs and review them to help others find a MOOC that suites them. But it is up to the user to go through these reviews and find out they would like to follow.

1.5 Research Problem

As more and more people across the world adopt e-learning platforms to increase their knowledge and gain certifications, Massive Open Online Courses have come to the spotlight for their openness and scale. Along with that, search engines and review sites solely focusing on MOOCs emerged to help people find MOOCs that belong their field of study easily.

However, the clear majority of services that offer MOOCs like Coursera, Edx and search engine platforms like Class Central only take a person's interest in a certain field of study or a certification into account when filtering or recommending MOOCs. However, a service called MOOCRec has done a great deal to bridge this gap between finding a MOOC that not only matches a person's field of study but also their personal learning style. Furthermore, MOOCs belong to a wide range of video styles in which they are delivered such as animations, presentation slides, etc.

This present a dilemma to a consumer as to which MOOC to choose since some video styles may appeal to a consumer more than the other.

While MOOCRec achieves many aspects of providing personalized recommendations based on individual learning styles, we have found a set of areas where the approaches can be further improved while introducing a new set of features to solidify the recommendation process by factoring in sentiments of MOOC consumers. To elaborate further, we identified that we can improve upon the process of identifying the individual learning style of a person which is done in terms of a lengthy questioner in the existing product, MOOCRec V1. Also,

Therefore, our research problem revolves around coming up with a more precise and elegant way to identify a person's individual learning style(s) and cover a broad range of MOOC video styles in order to increase the number of individual learning styles that can be supported by MOOCRec V2 service.

2. OBJECTIVES

2.1 General Objectives

The proposed solution is a research based implementation of a MOOC recommender that builds up upon MOOCRec V1 but extends its capabilities while streamlining the user experience, introducing new features that capture MOOC consumers' sentiments on discussion forums and identify a broader range of MOOC video styles while moving to a new architecture that focuses more on parallel processing to speed up the process of analyzing and recommending MOOCs.

To elaborate further, the objectives of this research can be outlined as follows.

- Help users identify their individual learning style(s) in an interactive, engaging, video-based tutorial that is short and specific.
- Recognize Machine Learning techniques applicable for scenarios that call for it and explore how they can be implemented to support the parallel processing architecture.
- Explore image processing and image recognition patterns and techniques.
- Integrate MOOC related online discussion spaces and ratings to solidify the recommendations made for each user.
- Index MOOCs that are presented in newer and complex video styles to create a broad spectrum of selections for video recommendations.

2.2 Specific Objectives

To achieve aforementioned general objectives, we have identified a range of specific objectives that have to be achieved in order to bring our proposed solution, which is MOOCRec V1 to fruition.

- Classify and index MOOCs that are delivered in video styles that are not covered by MOOCRec V1 such as
    - Animations
    - MOOCs with multiple video styles
- Decrease or eliminate false-positives that occur with certain styles of videos such as
    - False-positives involved with an image of a person being mistaken as a talking-head video.
    - False-positives involved with predicting that a video has code in it for text that is not code.

- Meta-data in forums within the MOOC platforms and from external discussion forums like Reddit will be analyzed to give a ‘forum score’ which can be used to recommend MOOCs especially to users who learn through peer-to-peer interactions.
- Users’ sentiments in forums within the platforms and from rating systems by services like Class Central where users have discussed about the course will be used to calculate a ‘course score’ which can be used when recommending MOOCs in addition to the other factors which are taken into account (learning styles, video type, etc.) to all users in general.
- Implement a facial expression analyzer to capture the engagement of a user.
- Create an engaging, introductory video that contains multiple MOOC learning material types throughout its runtime to be used to capture user’s engagement during each learning material type by using the aforementioned facial expression analyzer.
- Devise an architecture to classify videos parallelly in distributed computing environments to speed up the classification process and implement it.
- Provide basic user-profile related features and a dashboard to that each user can view their personalized recommendations.

3. METHODOLOGY

3.1 System Design

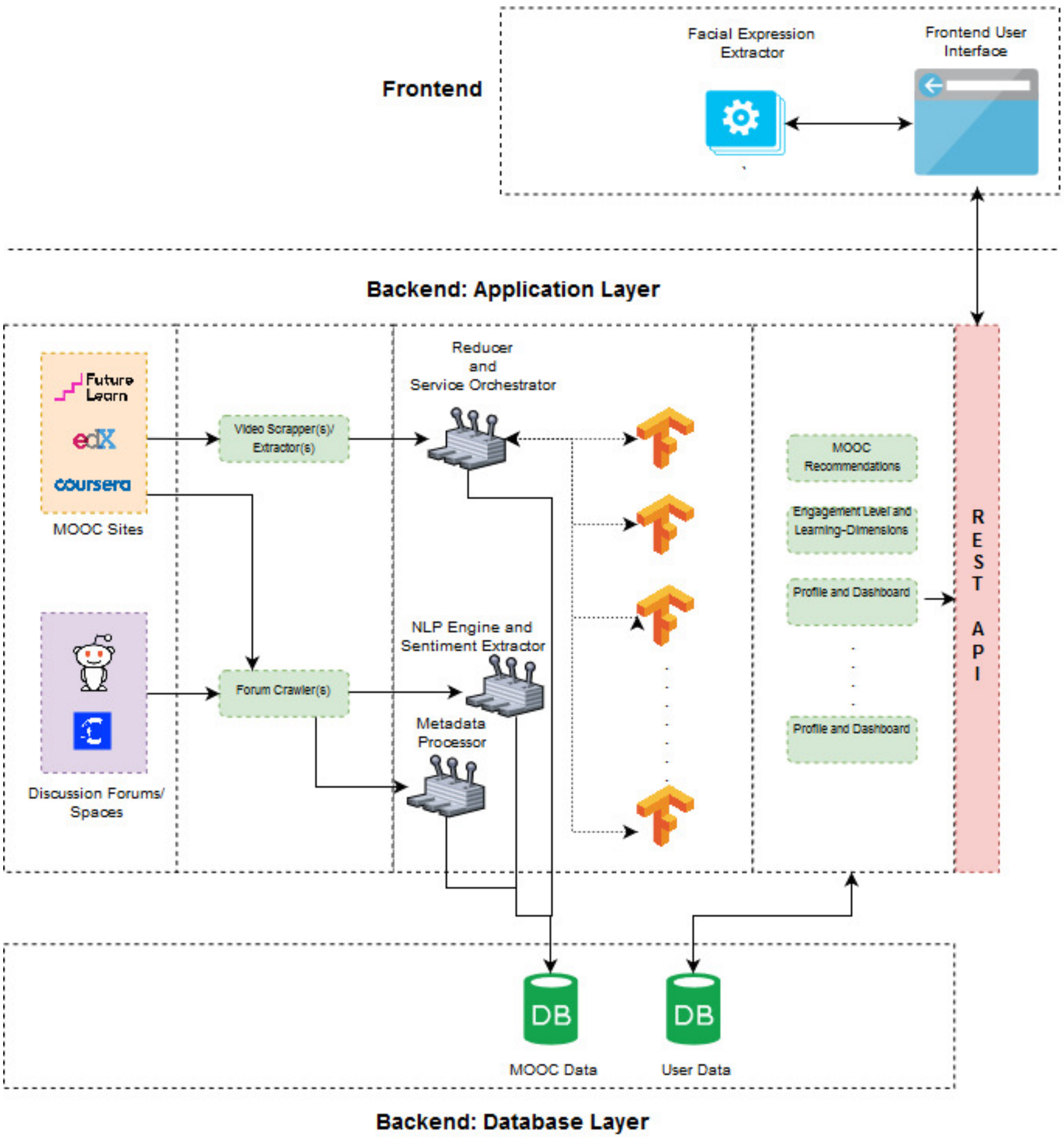

Figure 4:High Level System Design

3.2 System Description

The proposed system extends upon an already existing product which has been referred to as MOOCRec as well as MOOCRec V1 in order to distinguish our proposed system as MOOCRec V2. Our proposed system relies on analyzing a user's facial expressions to identify how engaged the user is with respect to different styles of videos by using Affective Model to score the engagement level. This model highlights the connection between a certain set of facial expressions and thDunderbore09.

The amount of engagement that a specific emotion can imply. Therefore, by detecting the facial expressions of a user by analyzing subtle cues in facial expressions, we can effectively determine the engagement level. MOOCs from popular MOOC sites such as Coursera, Edx, Futurelearn that fall into Information Technology, Science will be classified into different video styles that each video is delivered in.

The classification process is done parallelly by using multiple instances of the same classifier. These classifier-instances will be fed different frames from different videos while a service-orchestrator keeps track of which frame belongs to which video and at what time of the runtime. By doing so, the system becomes highly scalable due to its nature of independently classifying frames without any regard to where the frame is in the video.

Also, online discussion spaces and rating/review platforms offered by MOOC sites, MOOC search engines as well as other independent forums like Reddit will be periodically analyzed to extract information on MOOCs. While a web-crawler designed for each space/forum is responsible for extracting text, a suitably trained classifier will identify the sentiments such as whether the users prefer the MOOC that they are talking about or not and the amount of forum activity for a MOOC will be identified so that users who prefer to learn through peer-to-peer interaction can be suggested to them.

Finally, the data made by classifier-instances will be put together by the service-orchestrator to provide a meaningful conclusion about each MOOC that the system indexed; And the data from Online Discussion Sentiment Extractor and the Facial Expression Analyzer's conclusion on what the user's individual learning style(s) will be used to provide recommendations to each user to suite their individual learning style(s) and fields of studies.

Given its use of Machine Learning and parallel processing to achieve the implementation mentioned above, the system can be evaluated in following aspects.

- Accuracy of user-engagement evaluation.

  Give that the system uses facial expressions and a model based on facial expressions and engagement to predict the user's engagement with a specific learning material type, the accuracy of the prediction is, by far, the most important metric to evaluate. Although the Facial Expression Analyzer initially provides the engagement level per learning material type over the course of a video that contains multiple styles, we later map the highly-engaged learning material type(s) with learning style(s). Therefore, this can be evaluated in two ways;

- By letting a set of people freely choose their preferred learning material type(s) out of a list that contains the learning material type covered by our system, and then by analyzing the engagement-level predictions made for each user, we can identify if the system predicated high levels of engagement for the same learning material type(s) that the user freely selected initially.
- By letting the same set of people fill the ILS questionnaire to identify their learning style and allow them to interact with our intro video and asking them what learning material type(s) they most liked we can validate our proposed MOOC learning material-to-FSLSM mapping.

- Accuracy of classification.

  By feeding a set of evaluation/test data that consist of frames that depict different video styles from different MOOC sources, and comparing the predictions made by the classifier to the labels we provided along with the test data as to what each frame should be, we can measure the accuracy of the classifier.

- Speed.

  Given the use of parallel execution and service-orchestration to classify MOOCs, we can measure the not only the speed of classification but also how much has improved over sequential classification. We can use a single video clip, and measure the time taken to classify it on a single thread using a single instance of the classifier and the time taken to classify the same video parallelly using multiple instances of the classifier to find the improvement and the speed.

3.2.1 Identifying user's preferred learning style(s) and recommending suitable MOOCs.

To identify user's learning style in a more practical manner, the proposed system is replacing the ILS questionnaire which helped user identify the learning style with an introductory video which will be identifying user's preference by tracking user engagement.

In the initial phase, the proposed system will display an interactive introductory video which consists of all MOOCs learning material types that are recognized by the proposed system such as animations, talking head, presentation slides, etc. that are suitable for all types of learners.

In the next phase, emotion extraction by using facial recognition patterns will be considered. The end goal is to identify the user engagement based on emotions expressed on the user's face.

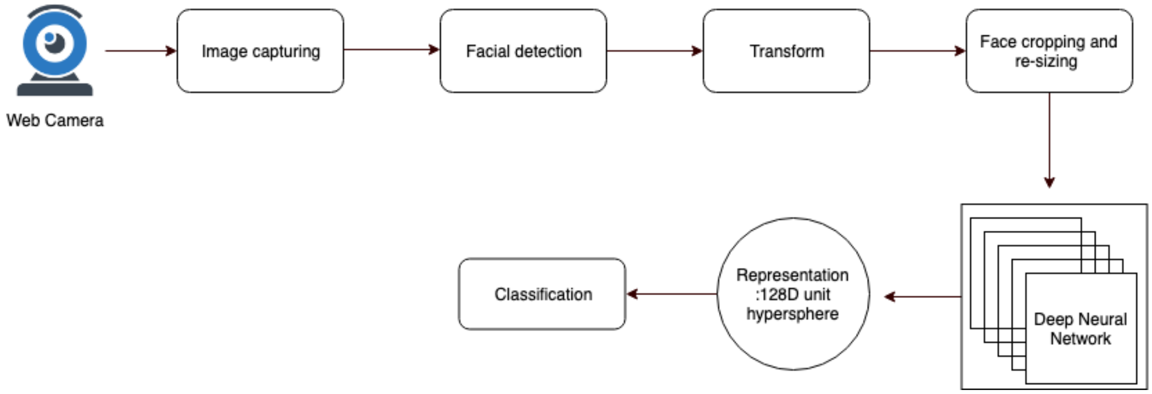

Figure 5: High Level Flow of Classifying Facial Expressions

Going forward with the facial expression recognition procedure in Figure 5, for image capturing, OpenCV, which is the widely used pre-trained model for expression analysis, will be used whereas for facial detection which is carried out to find bounding boxes around faces, OpevCv's Haar feature-based Cascade Classifier is being used. Then to transform the detected face for the neural network, OpenCv's Affine Transformation will be used. This will help make eyes and bottom lip appear on the same location in every image hence the problems that arise when having facial pictures with different angles will be solved. As the next step, it will crop the detected image making sure it is square shaped and fixed in size. As the deep neural network, we will be using widely used VGG-16 pre trained model by Keras. Input features-to-vectors mapping using 128-dimensional embedding will be carried out as a representation of our pre trained model and this will be used as feature inputs during classification. The output will be a series of academic emotions user expressed while watching our interactive intro video.

After extracting the facial expressions using aforementioned procedure, the mostly expressed emotions during each sample learning material type representation in the introductory video will be identified. This effectively results in extracting the corresponding engagement level from the engagement-to-emotion map [15]. This affected model is produced by adapting Russell and Feldman model and literature studies [15] by considering only academic emotions [16].

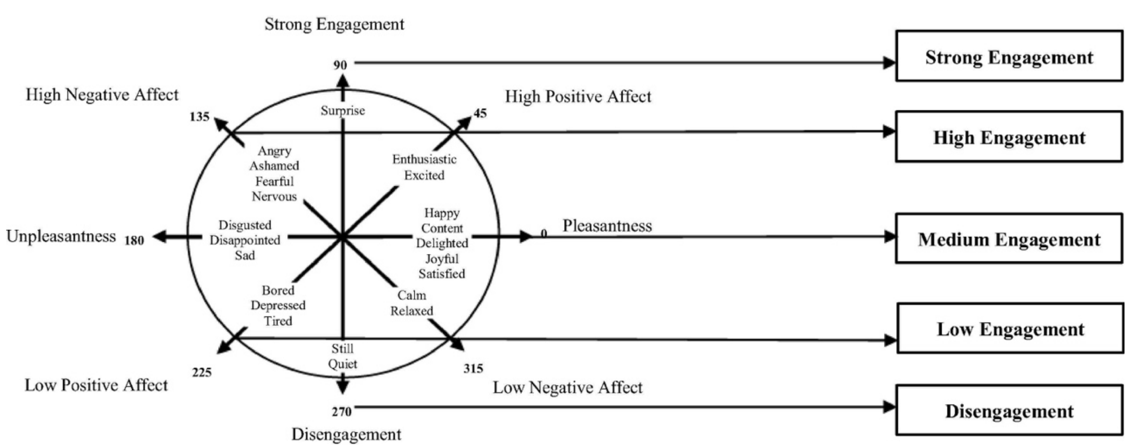

Figure 6: Academic Emotion to Engagement Level Mapping

Depending on engagement level as per the above diagram, the proposed system is able to decide what type of MOOC learning material type should be recommended for a given user. Finally, we will carry out a mapping of MOOCs with FSLSM in order to identify user's preferred learning style. We have added new combinations to the mapping to suit our learning material types and derived the mapping the below mapping [Table 3].

	Talking Head	Animation	Code/ Tutorial	Presentation slides	**Khan academy writing**	**Forum discussions**
Sensory			✓	✓	✓	✓
Intuitive	✓	✓				
Visual		✓		✓	✓	
Verbal	✓		✓	✓	✓	✓
Active			✓			
Reflective				✓		
Sequential			✓	✓		✓
Global	✓	✓				

Table 3: Learning-Dimension to Video Style Mapping based on FSLM

The measurable outcomes for this component are:

- Accuracy:
    - By letting a set of people freely choose their preferred learning material type(s) out of a list that contains the learning material types covered by our system, and then by analyzing the engagement-level predictions made for each user, we can identify if the system predicated high levels of engagement for the same learning material type(s) that the user freely selected initially.
    - By letting the same set of people fill the ILS questionnaire to identify their learning style and allow them to interact with our intro video and asking them what learning material type(s) they most liked we can validate our proposed MOOC learning material-to-FSLSM mapping.

3.2.2 Complex Video Classifier

Classification of MOOC video style into particular category is an important component of the proposed system. Type of a video style along with other materials can be an indicator of a specific learning style characteristics. Generally, the types of content in MOOC videos include: talking head, slides, coding, animations, conversations etc. In the production of some videos, there are lot of transitions between visual views, e.g.: switching from a talking head to a slide or switching from a slide to an animation. Automatic Boundary Detection via Sparse and Low-rank Decomposition and Image-based Convolutional Neural Networks (CNN) classification methods can be suitable approaches for this scenario based on the literature review.

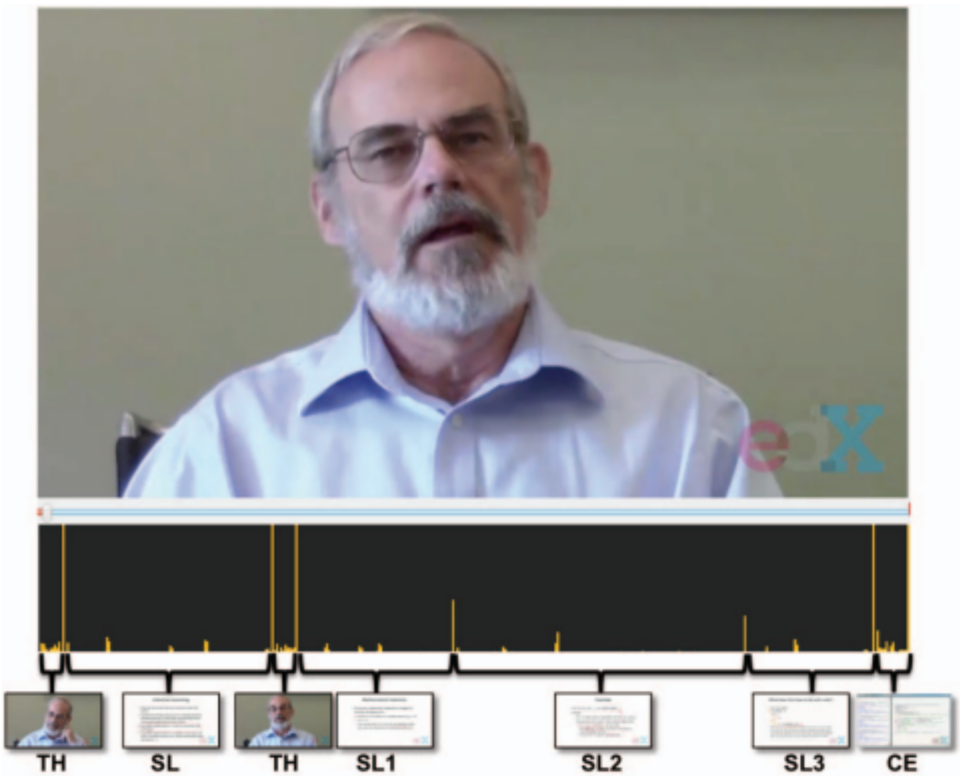

Figure 7: A MOOC video with multiple production styles. TH, SL, and CE stand for taking head, slides, and code examples respectively

Most existing shot segmentation methods concentrate on difference between consecutive frames. It has been demonstrated that embedding additional information, e.g. contextual information, in shot boundary detection would effectively reduce the influence of various disturbances. Thus, we focus on differences of all frames and propose a video shot segmentation based on low-rank and sparse matrix decomposition.

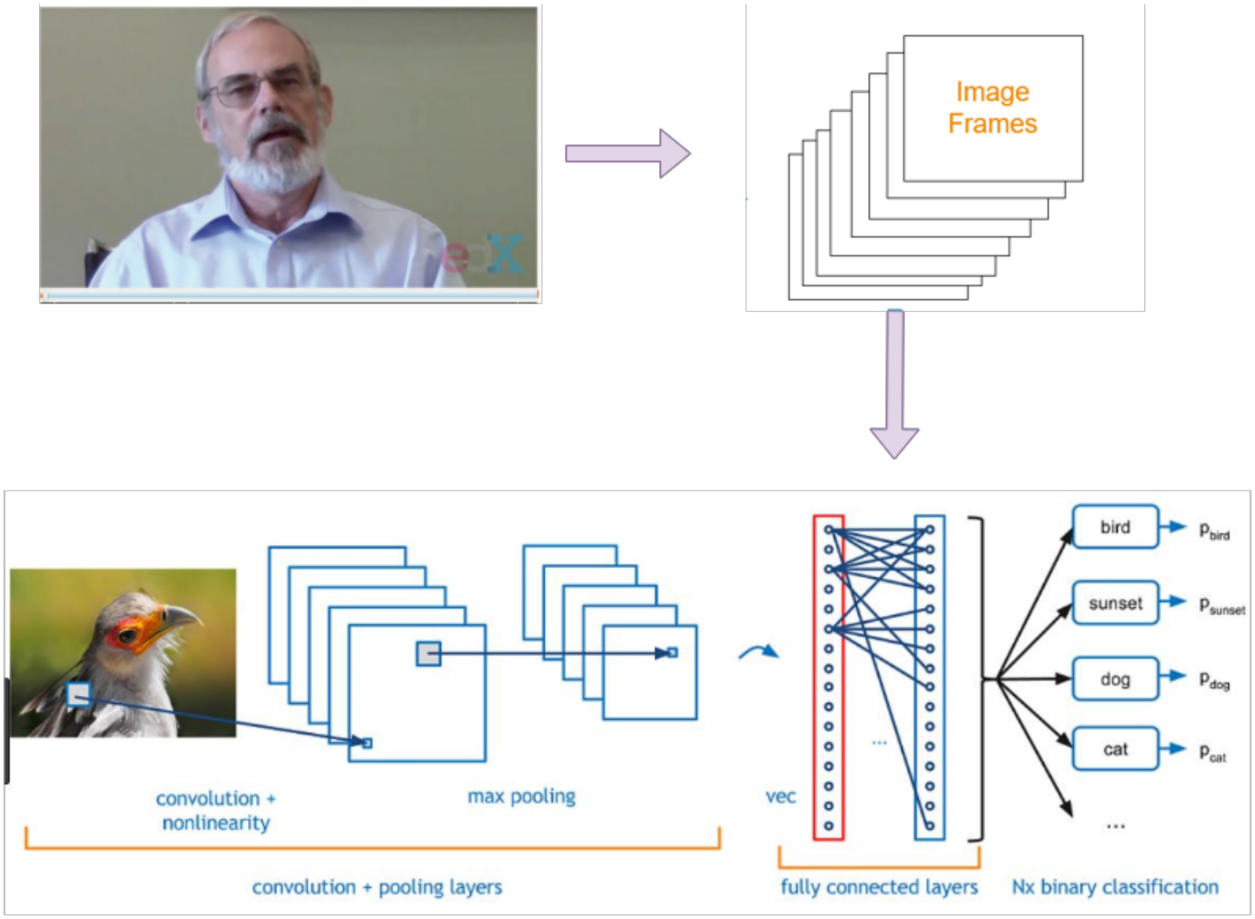

Figure 8: Frame based classification using CNN

Here, video is divided into keyframes/images and those images are passed to a CNN model. Then neural network will automatically learn the features of the images and prediction will be given.

The measurable outcomes for this component are:

- Accuracy: The accuracy of topic modeling can be measured by comparing the video styles classified by the neural network with the style actually contained in the given video, which can be determined manually.
- Speed: The speed of the algorithm can be measured by the amount of time taken to classify a given video(s) into set of production style categories.

3.2.3 Online forum thread discussion analysis to aid in recommending MOOCs

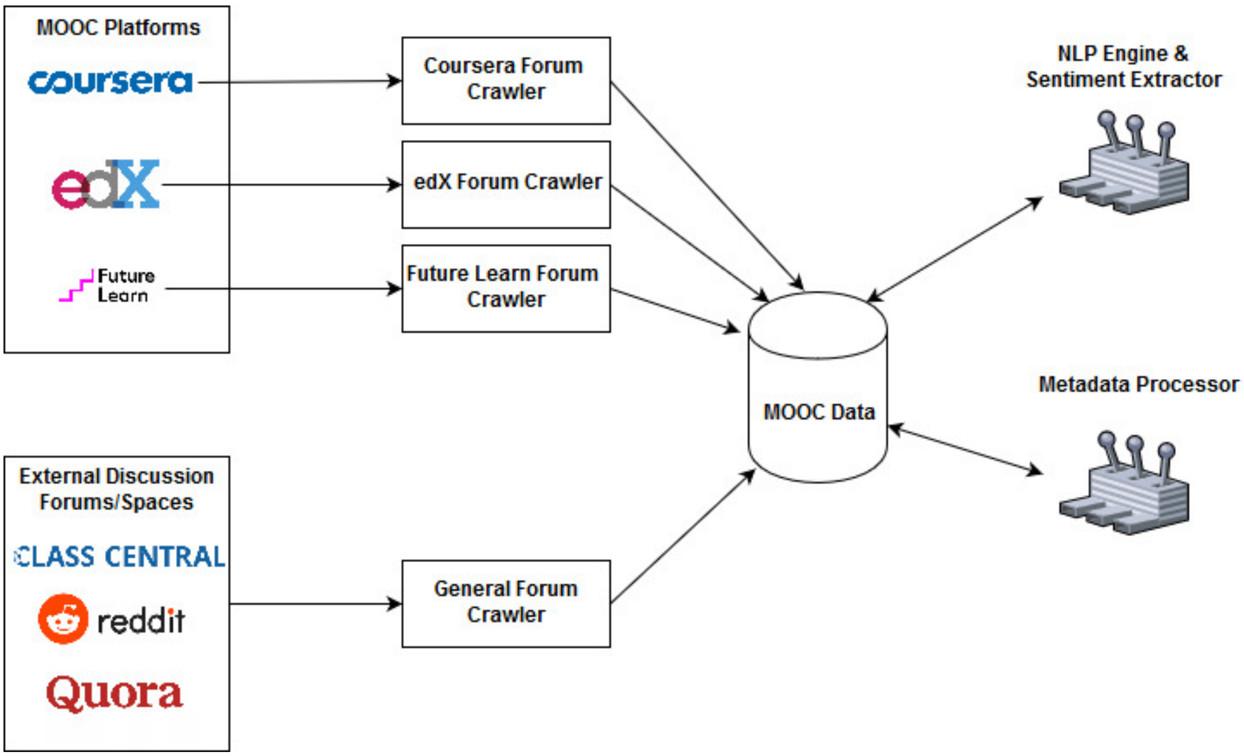

Figure 9: High Level Flow of Forum Analysis and Sentiment Extraction

The first phase of this part of the research would be to gather data from the range of different types of forums from within the MOOC platforms itself and from other external web sites. Platform specific web crawlers will have to be used to gather data from the MOOC sites and general web crawlers will be used to gather data from external sites. The reason for creating platform-specific crawlers is because MOOC platforms differ greatly from each other and so a general web crawler will not be as effective.

The second phase will be to analyze the data gathered to produce a meaning output. Sentiment analysis will be done to analyze messages where users have discussed about the quality of the course and will be used to calculate the course score. Metadata contained within forums will be used to calculate the forum score. The differences in the amount of information which was available for MOOCs from different platforms will have to compensated by readjusting the two scores.

Since the course and forum scores have been calculated for MOOCs of different platforms it can be used when recommending MOOCs to users. The course score will be considered when suggesting MOOCs to all users and the forum score will be used when recommending to users who have an affinity towards learning by peer-to-peer interactions.

The measurable outcome(s) of this component of the research is/are

- Accuracy – The accuracy can be measured by testing the results of the system without this component and the results gotten by integrating this component. The two results can then be compared with each other to check whether there was an increase in accuracy.

3.2.4 Service Orchestrator for Parallel Classification

The initial phase is to containerize the classifier. This involves setting up a docker image that is;

1. Highly lightweight
    - So that new instances of the classifier can be started up within seconds.
    - Utilizes less resources to stay active, thus yielding more resources for processing.
2. Machine Learning compatible
    - Ensure that all required libraries for image classification are present.

This gives a fully isolated virtual environment that is capable of scaling to even hundreds of classifier instances.

The next phase involves implementing an orchestrator that is capable of breaking work down to smaller tasks, coordinating these tasks among all available containers, analyzing the outputs given by the containers to reach a conclusion on a per-video basis. The orchestrator servers two important functionalities.

1. Task reduction
    - Assign each classifier instances with what frames to analyze and store the metadata in memory to be used for making the final conclusions.
    - Store the predictions returned by the classifier instances in the memory.
2. Analyze the predictions
    - Go through data stored in the memory and it all frames of a specific video is classified, make one final conclusion for the entire video.

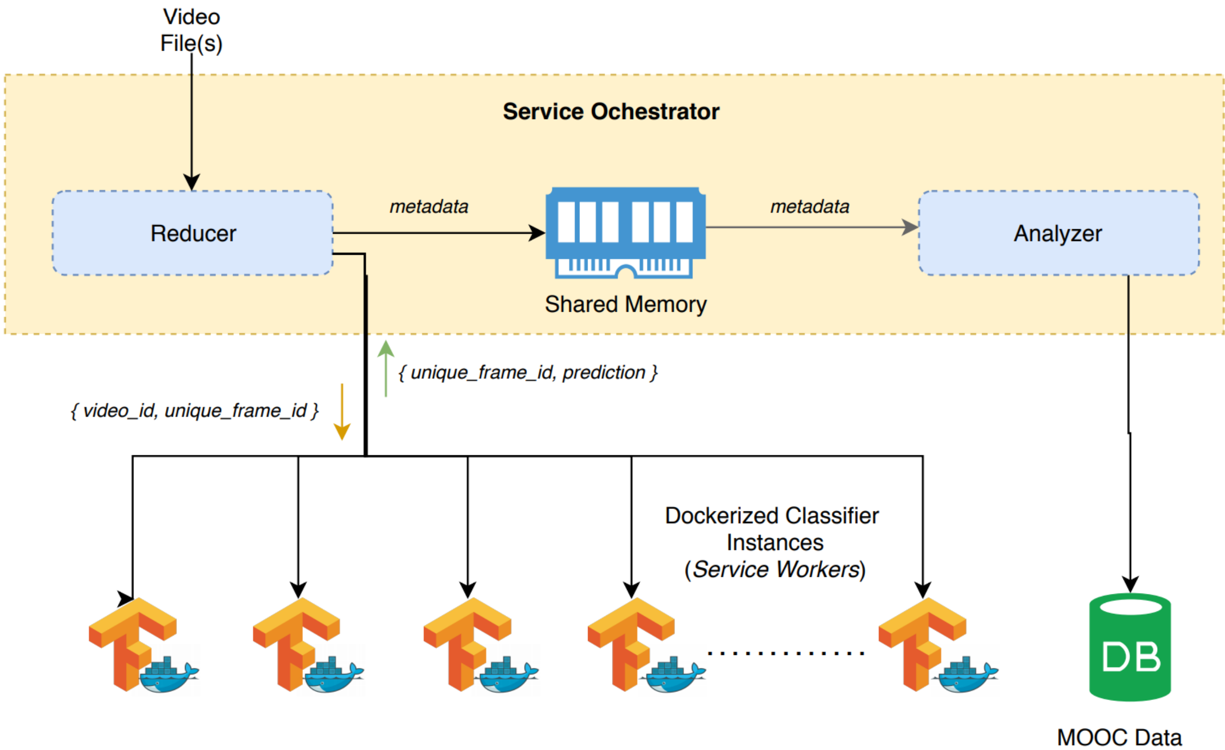

Figure 10: High Level Design of Service Orchestrator

3.3 Software Development Life Cycle

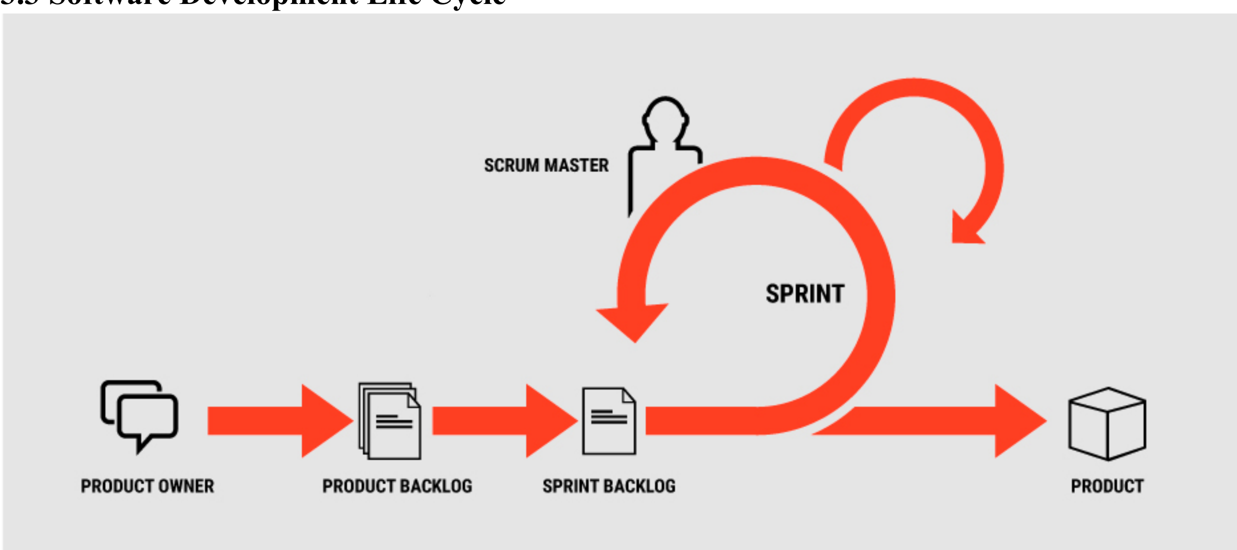

Figure 11: Agile Process [17]

Given the amount of new technologies and features associated with this research project, having to change directions often is unavoidable. Therefore, to facilitate such a dynamic process of developing a solution, a software development process such as Agile Scrum is paramount. Furthermore, the implementation is done by a small team of 4 undergraduates, thus daily scrum meetings and sprints that contains small chunks of functionalities to implement rapidly seem ideal. Also, the fact that Agile Scrum encourages customer feedback throughout the implementation goes hand in hand with bi-weekly supervisor meetings that will be held between the research group and the supervisor, co-supervisor. Therefore, when all these facts are considered, following Agile Scrum practices seems ideal for this research project.

3.4 Gantt Chart

The research and implementation project can be identified as a collection of sub-tasks that are outlined in the following Gantt chart along with the expected time each sub-task would take, in order to bring MOOCRec V2 to fruition.

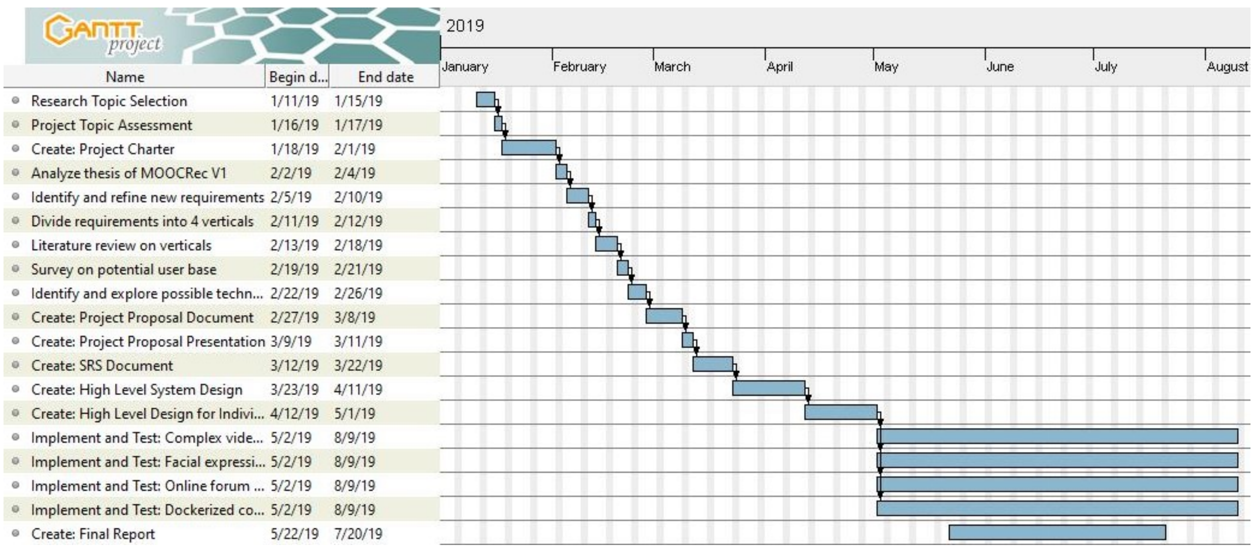

Figure 12: Gantt Chart

3.5 Work Breakdown Structure

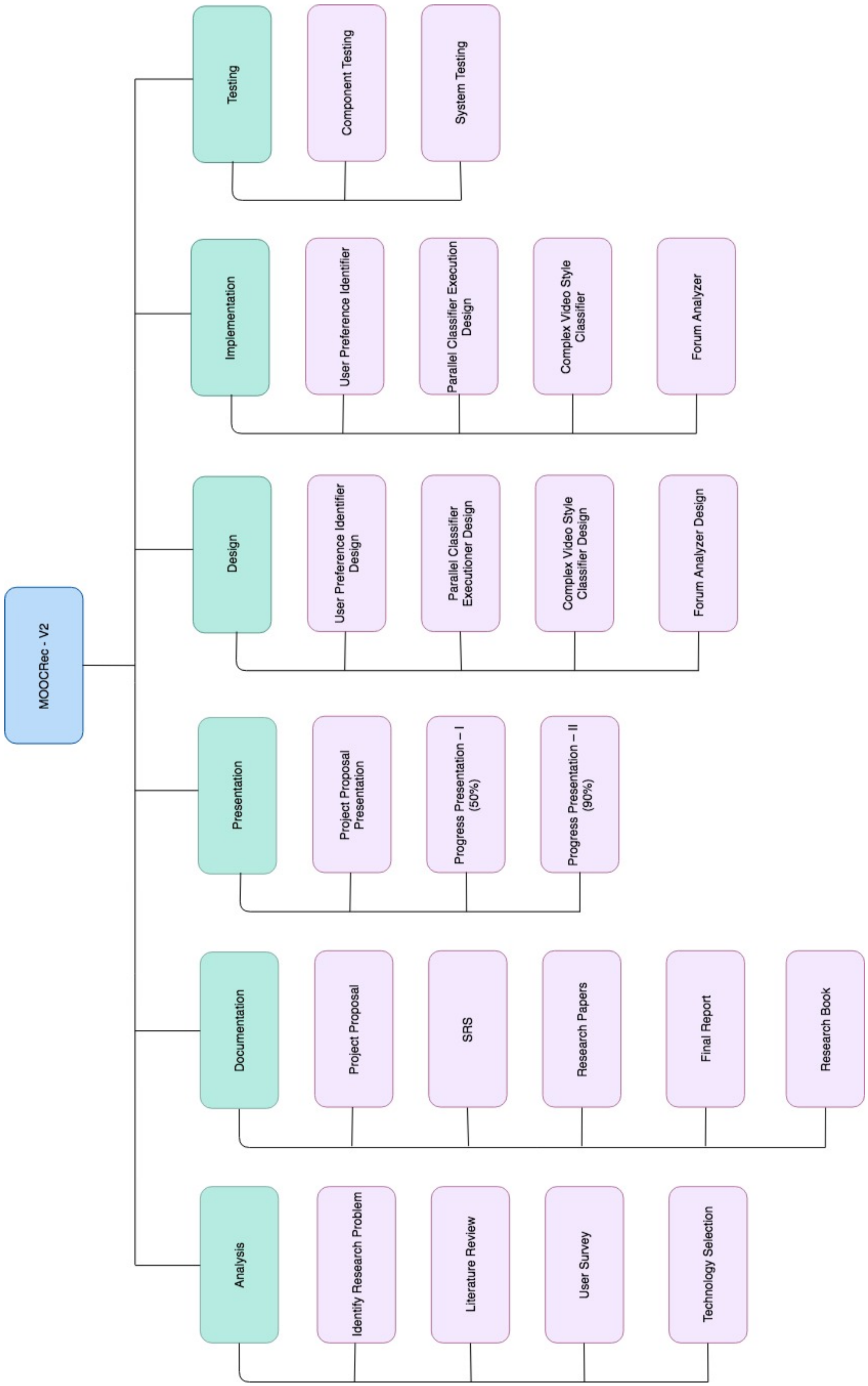

Figure 8: Work Breakdown Structure

3.6 Proposed Tools and Technologies

For exploring the most ideal solution for each feature and to test the implemented features, we plan to use the following set of tools and technologies.

Tools and Services

- Google Colab

  A free collaboration platform offered by Google to facilitate Python programming, while also specializing in Machine learning and Deep Learning aspects. This platform provides optimized hardware such as GPUs for testing Machine Learning implementations.

- Jupyter

  Another open-source service that provides an interactive environment for coding and testing a range of programming languages.

- Big ML

  A platform with a free-tier that allows training and testing out Machin Learning models.

- AWS Free-Tier

  Amazon Web Services, which is the biggest cloud provider, offers a free-tier that provides most of the functionality that the paid tiers get, but with certain limitations surrounding the usage. For running Docker and Kubernetes clusters and testing out parallelized final product, AWS can come handy.

Technologies

- Python
- Keras
- TensorFlow
- Scikit
- VGG16
- MongoDB
- NodeJS
- HTML5 + CSS3

4. DESCRIPTION OF PERSONAL AND FACILITIES

Student Name	Student ID	Task Description
Liyanage A.Y.K.	IT 16 0327 98	• Develop a self-contained, light-weight API to run in conjunction with the classifier. • Integrate the API and the classifier to work together. • Containerize the above implementations using a light-weight Docker Image suitable for Python and Machine Learning applications. • Implement a task reducer to break down the workload that each classifier instance has to process. • Implement an analyzer to put together the outputs given by multiple instances of the classifier to arrive at a final conclusion. • Deploy the containerized cluster of classifiers and the service orchestrator (task reducer + analyzer) in distributed compute instances/servers. • Create Documentation. • Unit and component testing. • Evaluate performance improvement of switching from single threaded to parallel processing architecture.
De Silva W.A.T.P.	IT16051980	• Implement a facial expression extractor in the frontend of the application. • Implement the mapping logic that provides the engagement level based on the facial expression. • Implement the mapping logic that provides the learning-dimension/style based on the video styles that the user was highly engaged with. • Implement and train the classifier responsible for identifying facial expressions/emotions. • Devise an interactive introductory video that contains all the video styles that MOOCRec V2 classifies. • Create Documentation. • Unit and component testing.
Pathirana P.H.P.S.L.	IT16004382	• Implement a classifier capable of identifying a broad range of video production styles. • Train the model using a large scale of data. • Create Documentation • Unit and component testing.

<table>
<tr><td></td><td></td><td>Evaluate prediction accuracy and false-positive percentage.</td></tr>
<tr><td>Hilmy S.B.M.</td><td>IT16005372</td><td>Implement forum-crawlers for following online discussion spaces;
MOOC Platforms (Coursera, edX, Future Learn)
External sites (Class Central, Reddit, Quora)
Implement a Natural Language Processing based classifier to extract the context of a forum thread.
Identify and map forum threads and MOOCs.
Implement a sentiment extractor to identify the sentiments expressed by users in forum threads.
Implement a rating extractor.
Implement a scoring formula to calculate a score for each MOOC course based on above forum-based metrics.
Create Documentation.
Unit and component testing.</td></tr>
</table>

Table 4: Individual Roles and Tasks

5. BUSINESS POTENTIAL

While MOOCRec V1 gained a considerable amount of business interests, we believe, by further improving and extending its capabilities and re-architecting the core system in MOOCRec V2, we will be able to present our proposed solution, MOOCRec V2 as a business-ready application. Thus, it is worth noting that the following aspects of MOOCRec V2 can be used to promote its business value.

- Integration with major players of MOOCs such as Coursera, Futurelearn, Edx without any implementation from their end.
- Integration with online discussion forums to analyze how actual users across the world react to different MOOCs on different platforms to provide a context to a potential user, without any implementation from discussion forums' end.
- Given that the system recommends MOOCs that are suitable for each individual, the completion rate of MOOCs discovered by our system can increase; this can provide a favorable and effective platform for MOOC providers to advertise.
- Being architected to be highly scalable and distributed, all the financial advantages of a scalable platform is present in our system, such as scaling down to lower the cost when the new MOOCs count is low, utilizing all the resources available in servers which ensures more MOOCs are classified during the servers' uptime.

6. BUDGET AND BUDGET JUSTIFICATION

For the majority of testing and implementing workflows, free and open-sourced solutions will be used such as Google Colab, Jupyter, BigML. Furthermore, for testing the actual implementation of MOOCRec V2, cloud-based infrastructure that falls under AWS Free-Tier will be utilized. This choice of free and open-source technologies gives us a zero-cost implementation platform during the initial stages.

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8. APPENDICES

Do you like if an online learning platform automatically identifies your learning style or to fill a questionnaire and identify your learning style?

45 responses

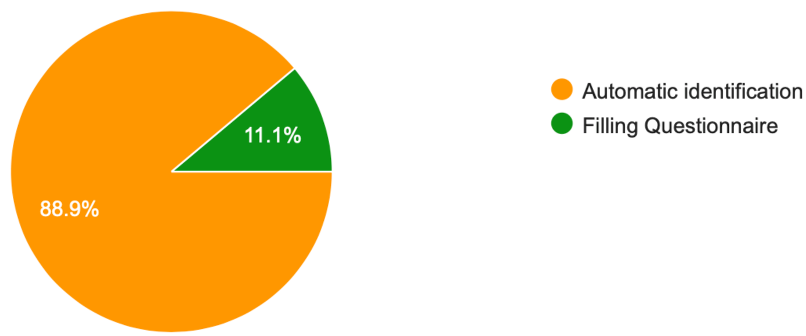

Figure 9: Survey on Filling a Questioner

Do you like allowing the online learning platform to analyze your facial expressions only once by turning on your webcam and watch a video of 5-10 minutes to help you automatically identify your learning style given that your data is not shared with any other party?

40 responses

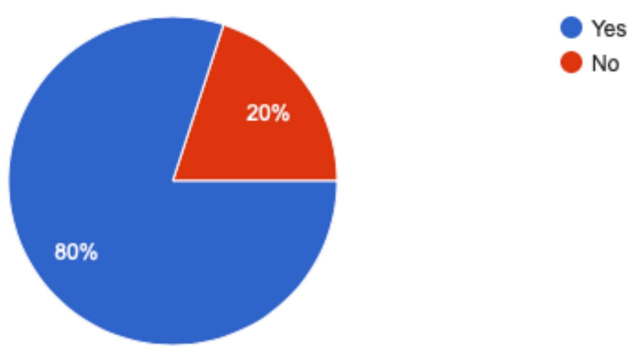

Figure 10: Survey on Users' Willingness to Provide Temporary Web Cam Access