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Face Recognition Based Student Attendance System

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Abstract: *The term 'biometrics' refers to a measurable characteristic that is unique to an individual such as fingerprints, facial structure, the iris or a person's voice. This project presents a face image based biometric system that records the attendance of a person by using a hand held face image biometrics. Attendance is a concept that exists in different places like institutions, organization's, hospitals, etc. during the start and end of the day to mark a person's presence. In early days and even now in many places attendance is recorded manually in attendance registers by calling out the names. This results in waste of time and human effort. Also there are many fraudulent issues that happen when we use a register. A student attendance system using face recognition and Grassmann classification is a biometric system that can automate the attendance taking process in a classroom setting. This system involves collecting a dataset of images of each student in the classroom and using face detection and alignment algorithms to detect and align the faces in each image. The Grassmann classification algorithm is then used to extract features from the images and classify them as belonging to a particular student. When a student enters the classroom, their face is captured by a camera and compared to the images in the dataset. If a match is found, the student is marked as present. This system has the potential to save time and increase accuracy in the attendance taking process. However, it also raises concerns about privacy and the security of the collected data. Proper safeguards must be put in place to ensure that the system is used ethically and responsibly.*

Keywords: Face Registration, Student Details Maintenance, Real Time Face Capture, Feature Extraction, Grassmann Learning, Feature Classification, Mark Attendance, Alert System

I. INTRODUCTION

1.1 Video Surveillance System

Video surveillance is becoming more and more essential nowadays as society relies on video surveillance to improve security and safety. For security, such systems are usually installed in areas where crime can occur such as banks and car parks. For safety, the systems are installed in areas where there is the possibility of accidents such as on roads or motorways and at construction sites. Currently, surveillance video data is used predominantly as a forensic tool, thus losing its primary benefit as a proactive real-time alerting system. The fundamental problem is that while mounting more video cameras is relatively cheap, finding and funding human resources to observe the video feeds is very expensive. Moreover, human operators for surveillance monitoring rapidly become tired and inattentive due to the dull and boring nature of the activity. There is a strong case for automated surveillance systems where powerful computers monitor the video feeds — even if they only help to keep human operators vigilant by sending relevant alarms. Smart cameras can improve video surveillance systems by making autonomous video surveillance possible. Instead of using surveillance cameras to solve a crime after the event, a smart camera could recognize suspicious activity or individual faces and give out an alert so that an unwanted event could be prevented or the damage lessened. From another perspective, smart cameras reduce the need for human operators to continually monitor all the video feeds just to detect the activities of interest, thus reducing operating costs and increasing effectiveness.

Smart Cameras

Smart cameras are becoming increasingly popular with advances in both machine vision and semiconductor technology. In the past, a typical camera was only able to capture images. Now, with the smart camera concept, a camera will have the ability to generate specific information from the images that it has captured. So far there does not

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seem to be a well-established definition of what exactly a smart camera is. In this paper, we define a smart camera as a vision system which can extract information from images and generate specific information for other devices such as a PC or a surveillance system without the need for an external processing unit. Figure 1 shows a basic structure of a smart camera. Just like a typical digital camera, a smart camera captures an image using an image sensor, stores the captured image in the memory, and transfers it to another device or user using a communication interface. However, unlike the simple processor in a typical digital camera, the processor in a smart camera will not only control the camera functionalities, but it is also able to analyse the captured images to obtain extra information.

Video Processing

Video signal is basically any sequence of time varying images. A still image is a spatial distribution of intensities that remain constant with time, whereas a time varying image has a spatial intensity distribution that varies with time. Video signal is treated as a series of images called frames. An illusion of continuous video is obtained by changing the frames in a faster manner which is generally termed as frame rate. The demand for digital video is increasing in areas such as video teleconferencing, multimedia authoring systems, education, and video-on-demand systems.

1.2 Person Identification

Person re-identification is the task of matching individuals across different cameras in a multi-camera surveillance system. It is a challenging problem due to the large variations in appearance caused by factors such as pose, illumination, occlusion, and camera viewpoint. The goal of person re-identification is to associate the same person's identity across different cameras, which can be used for various applications such as video surveillance, crowd analysis, and tracking individuals in public spaces. Recent advances in deep learning and computer vision have led to significant progress in person re-identification, making it a promising area of research for real-world applications.

1.3 Face Recognition Based Person Identification

Face recognition is one of the most widely used techniques for person identification, which involves analyzing facial features and matching them against a database of known faces to identify the individual. It is a non-intrusive and relatively fast method of identification that can be used in various applications such as security systems, access control, and law enforcement.

There are two main approaches to face recognition: feature-based and holistic. Feature-based methods involve extracting specific features such as eyes, nose, and mouth from an image and using them to compare against a database of known faces. Holistic methods, on the other hand, analyze the entire face as a single entity and use advanced techniques such as deep learning to match against a database.

Recent advancements in deep learning and convolutional neural networks (CNNs) have led to significant improvements in face recognition accuracy. These methods can learn powerful representations of faces and can handle variations in lighting, pose, and expression. However, there are still challenges in face recognition such as variations in age, ethnicity, and changes in appearance due to plastic surgery or aging, which require further research and development.

1.3.1 Steps Involved in Face Recognition

Face detection: The first step is to detect faces in the input image or video frame. This involves using algorithms that can identify the presence of a face in an image and locate its position.

Face alignment: Once a face is detected, it needs to be aligned so that the features of the face are in a consistent position and scale. This step involves aligning the detected face to a standard reference frame.

Feature extraction: The next step is to extract features from the aligned face. These features can include geometric features such as distances between facial landmarks or appearance-based features such as texture, color, and shape.

Face matching: Once features are extracted from the input face, they can be compared to features from a database of known faces. This step involves finding the closest match between the input face and the faces in the database.

Face identification: Finally, the identity of the person in the input image or video frame can be determined by comparing the matched face to a database of known identities.

1.4 Machine Learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.

The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

II. RELATED WORK

Tang, Yingzhi, et.al [1]proposed an image domain-to-domain translation method by keeping pedestrian's identity information and pulling closer the domains' distributions for unsupervised person re-ID tasks. Proposed work exploits the CycleGAN to transfer the existing labeled image domain to the unlabeled image domain. Under the framework of CycleGAN, propose two schemes to realize these two constraints, i.e., a Self-labeled Triplet Net and a maximum mean discrepancy. Firstly, the pair of real images are inputted into the CycleGAN for generating two fake domain images. Secondly, the pair of real images and fake images are fed into our Self-labeled Triplet Net, which takes image itself as label. Our Self-labeled Triplet Net is able to pull images with the same identity closer and push images with different identity away, thus commendably preserving the pedestrian's identity information. Subsequently, maximum mean discrepancy based distribution pulling is conducted. This approach is inspired by the unsupervised domain adaption where source domain is labeled while target domain is unlabeled. To empower the domain adaption the ability of pulling and pushing domain distributions, we further introduce the maximum mean discrepancy into the CycleGAN. During the translation process, the value of maximum mean discrepancy between fake image and target image will be computed for pulling domain distribution closer.

Jiang, et.al [2]proposed an endto-end Self-supervised Agent Learning (SAL) algorithm for unsupervised person Re-ID by jointly modeling the class label information in source domain, the similarity consistency in target domain, and the self-supervised constraint in cross domain in a unified deep model. To align domain distributions robustly, we design three effective learning mechanisms including supervised label learning in source domain, similarity consistency learning in target domain, and selfsupervised learning in cross domain, which play important roles in reducing the domain discrepancy for unsupervised person Re-ID. In the supervised label learning module, the original and reconstructed features of source domain are used to train a classification network to obtain the discriminative feature embedding for source domain and establish a relationship between the source domain and the agents. In the similarity consistency learning module, we explore an agentguided hard negative mining, which focuses on the pairs of visually similar but different persons in target domain and aims to distinguish them with the guidance of their similarity coefficients to agents.

Lin, et.al [3]presented an iterative framework which overcomes the camera variance and achieves across-camera similarity exploration. Specifically, we apply an unsupervised style transfer model to generate style-transferred training images with different camera styles. Then we iteratively exploit the similarity within the same identity from both the original and the style-transferred data. We start with considering each training image as a different class to initialize the Convolutional Neural Network (CNN) model. Then we measure the similarity and gradually group similar samples into one class, which increases similarity within each identity. Here also introduce a diversity regularization term in the clustering to balance the cluster distribution. The proposed framework with some specific design: (i) adopt repelled loss to optimize the CNN model without labels. In the beginning, the repelled loss directly learns to discriminate between individual images that maximize the diversity among training images. As the images are merged into clusters, the repelled loss learns to minimize total intra-cluster variance and maximize the inter-cluster variance. (ii) In practice, different identities should have a similar probability to be captured by cameras, and thus the image number for different clusters should be balanced.

Lin, Shan, et.al [4] implemented a multi-dataset feature generalization network (MMFA-AAE), which is capable of learning a universal domain-invariant feature representation from multiple labeled datasets and generalizing it to

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'unseen' camera systems. The network is based on an adversarial auto-encoder to learn a generalized domain-invariant latent feature representation with the Maximum Mean Discrepancy (MMD) measure to align the distributions across multiple domains. Here proposed a novel framework for domain generalization, which aims to learn a universal representation via domain-based adversarial learning while aligning the distribution of mid-level features between them. Our proposed framework can be considered as an extension of our Multitask Mid-level Feature Alignment (MMFA) network in a multiple domain learning setting. We called it MMFA with Adversarial Auto-Encoder (MMFA-AAE). Our MMFA-AAE can simultaneously minimize the losses of data reconstruction, identity, and triplet loss. It alleviates the domain difference via adversarial training and also matches the distribution of midlevel features across multiple datasets.

Feng, et.al [5] proposed a joint learning framework to learn better feature embeddings via high precision neighbor pseudo labels and high recall group pseudo labels. The group pseudo labels are generated by transitively merging neighbors of different samples into a group to achieve higher recall. However, the merging operation may cause subgroups in the group due to imperfect neighbor predictions. To utilize these group pseudo labels properly, we propose using a similarity-aggregating loss to mitigate the influence of these subgroups by pulling the input sample towards the most similar embeddings. The predicted neighbors are not perfect and may contain some negative samples with a different identity due to similar backgrounds or frequent pedestrian occlusions. Merging the neighbors of these negative samples into one group makes the group noisy. Thus a group may contain multiple subgroups corresponding to multiple identities, as shown in Figure. 1. This inherent structure of the merged group is the main difference with clusters generated by DBSCAN. Considering subgroups in the merged group, we hope the input sample to be closer to the most similar subgroup than other subgroups to mitigate their influence. Hence we introduce a similarity-aggregating loss based on the assumption that with a good embedding function, the embeddings which share the same identity should be closer than the embeddings with different identities.

Ye, Mang, et.al [6] implemented a Dynamic Graph Matching (DGM) framework, which improves the label estimation process by iteratively refining the graph structure with better similarity measurement learnt from intermediate estimated labels. In addition, we design a positive re-weighting strategy to refine the intermediate labels, which enhances the robustness against inaccurate matching output and noisy initial training data. To fully utilize the abundant video information and reduce false matching, a co-matching strategy is further incorporated into the framework. A dynamic graph matching (DGM) framework is introduced to refine the label estimation process for unsupervised video re-ID. Specifically, our framework includes an iterative updating process, where a one-toone graph matching problem is solved at each iteration. Labels are then extracted with graph matching output. Meanwhile, graph construction is dynamically updated by learning an improved distance metric with the intermediate labels.

Lin, Yutian, et.al [7] presented a new framework of unsupervised learning in which clustering is no longer required, and thus the error of the hard quantization loss is relieved. Specifically, our framework adopts a classification network with softened labels, where the softened labels reflect the image similarity. Unlike the original one-hot labels that force images belonging to an exact class, we treat the labels as a distribution, that an image is encouraged to be associated with several related classes. For each training data, the network is trained not only to predict the ground-truth class, but motivated to predict the similar classes. The learned embedding is then closes to similar ones and has a long distance from irrelevant images. To relieve the issue of camera variance, we propose the cross-camera encouragement term (CCE) that promotes the softened similarity learning from images under different camera views. In this way, the model will learn from more diverse data. Note that the camera ID is automatically obtained at the moment of capturing and is no need for human labeling. Moreover, we extract part features and consider the partial details along with the global appearance as an additional clue.

Ge, Yixiao, et.al [8] provided a novel self-paced contrastive learning framework with hybrid memory. The hybrid memory dynamically generates source-domain class-level, target-domain cluster-level and un-clustered instance-level supervisory signals for learning feature representations. Different from the conventional contrastive learning strategy, the proposed framework jointly distinguishes source-domain classes, and target-domain clusters and un-clustered instances. Most importantly, the proposed self-paced method gradually creates more reliable clusters to refine the hybrid memory and learning targets, and is shown to be the key to our outstanding performance. Proposed method has shown considerable improvements over a variety of unsupervised or domain adaptive object re-ID tasks. The supervised performance can also be promoted labour-free by incorporating unlabeled data for training in our framework. The core is at exploiting all available data for jointly training with hybrid supervision. Positive as the results are, there still exists a gap from the oracle, suggesting that the pseudo-class labels may not be satisfactory enough even with the proposed self-paced strategy.

Chen, et.al [9] implemented method incorporates generative and contrastive modules into one framework, which are trained jointly. Both modules share the same identity feature encoder. The generative module disentangles identity and structure features, then generates diversified novel views. The novel views are then used in the contrastive module to improve the capacity of the shared identity feature encoder, which in turn improves the generation quality. Both modules work in a mutual promotion way, which significantly enhances the performance of the shared identity feature encoder in unsupervised ReID. Moreover, proposed method is compatible with both UDA and fully unsupervised settings. Proposed generative and contrastive modules mutually promote each other's performance in unsupervised ReID. Moreover, this framework does not rely on a source dataset, which is mandatory in style transfer based methods. Extensive experiments on three datasets validate the effectiveness of our framework in both unsupervised person ReID and multi-view person image generation.

He, Kaiming, et.al [10] presented Momentum Contrast (MoCo) for unsupervised visual representation learning. MoCo provides competitive results under the common linear protocol on ImageNet classification. More importantly, the representations learned by MoCo transfer well to downstream tasks. MoCo can outperform its supervised pre-training counterpart in 7 detection/segmentation tasks on PASCAL VOC, COCO, and other datasets, sometimes surpassing it by large margins.A main purpose of unsupervised learning is to pre-train representations (i.e., features) that can be transferred to downstream tasks by fine-tuning. Proposed process show that in 7 downstream tasks related to detection or segmentation, MoCo unsupervised pre-training can surpass its ImageNet supervised counterpart, in some cases by nontrivial margins. In these experiments, we explore MoCo pre-trained on ImageNet or on a one-billion Instagram image set, demonstrating that MoCo can work well in a more real-world, billionimage scale, and relatively uncurated scenario. These results show that MoCo largely closes the gap between unsupervised and supervised representation learning in many computer vision tasks, and can serve as an alternative to ImageNet supervised pre-training in several applications.

2.2 Existing Methodologies

Existing work explains a novel group sampling for pseudo-label-based unsupervised person re-ID, which utilizes the grouping operation and solves the shortcomings in triplet sampling. Grouping samples helps to optimize the model in a direction consistent with the trend of the whole class and to reduce the impact of a single sample, which facilitates similarity structure maintenance within each class. At the same time, using the overall trend of the class also helps to maintain discrimination between classes, thereby preventing many classes from being merged, which inhibit the model from deteriorated over-fitting. In this way, the model has access to exploit more subtle differences from the existing similarity structure so as to extract the unique identity similarity.

Traditional methods of attendance tracking such as manual entry, paper-based attendance sheets, barcode readers, and biometric scanners are time-consuming and error-prone. A manual student attendance system involves physically taking attendance by calling out each student's name and recording their presence or absence in a register or sheet of paper. To overcome these limitations, face recognition-based attendance systems have emerged as a viable alternative.

2.3 Problems in Manual Attendance System

Time-consuming: Taking attendance manually is a time-consuming process, especially if there are a large number of students to be accounted for. It can also cause disruptions to the class and interfere with the learning process.

Error-prone: Manual attendance systems are prone to errors, especially if the teacher or administrator is distracted or absent-minded. Incorrect entries in the register can result in inaccurate attendance records, which can cause problems later on.

Limited accuracy: Manual attendance systems do not provide accurate data on the exact time that students arrive or leave the class. This can be a problem if the school or institution needs to track attendance for specific periods or purposes.

Difficulty in data analysis: Manual attendance systems make it difficult to analyze attendance data, as the data is often stored in paper format. This can make it challenging to identify patterns or trends in attendance, which can be useful for decision-making.

Lack of accountability: Manual attendance systems lack accountability, as it is difficult to verify whether the attendance records are accurate or not. This can lead to issues such as students falsely claiming attendance, or teachers manipulating attendance records for their benefit.

2.4 Face Recognition based Attendance System using Grassmann Learning

Attendance tracking is an important process in schools, colleges, and workplaces to keep track of the attendance of students or employees. Face recognition-based attendance systems are becoming increasingly popular due to their accuracy, speed, and convenience. These systems use advanced facial recognition software to identify and authenticate individuals. The system captures an image of the individual's face, compares it with the pre-stored images of the individuals in the database, and marks attendance if a match is found. Face recognition based attendance system is a modern technology that uses facial recognition software to identify and authenticate individuals for attendance tracking purposes. In this system, an image of the individual's face is captured and compared with the pre-stored images of the individuals in the database. This attendance system utilizes grassmann algorithm for feature extraction and classification process. The captured face image was processed using grassmann algorithm. The extracted features are represented in a feature vectors as matrix representation model. These vectors are classified with feature vectors presented in student's database. If a match is found, attendance is marked for that individual. The use of face recognition technology for attendance tracking has many advantages over traditional methods. It eliminates the need for manual processes and reduces the chances of errors. It also provides real-time data and analytics that can be used for better decision-making.

III. METHODOLOGY

3.1 Grassmann Learning Algorithm

Representing the facts on Grassmann manifolds is famous in some image and video recognition responsibilities. In unique, here design complete rank mapping layers to convert input Grassmannian records into extra desirable ones, make the most orthogonal re-normalization layers to normalize the ensuing matrices, observe projection pooling layers to reduce the version complexity in the Grassmannian context, and devise projection mapping layers to show the ensuing Grassmannian information into Euclidean forms for ordinary output layers. To train the deep community, this make the most a stochastic gradient descent placing on manifolds in which the connection weights are living on, and have a look at a matrix generalization of returned propagation to replace the established statistics. The famous packages of Grassmannian records inspire us to construct deep neural network architecture for Grassmannian representation studying. For this motive, the new community architecture is designed to take Grassmannian statistics at once as enter, and learns new favorable Grassmannian records which might be able to improve the final visual responsibilities. In other phrases, the new community pursuits to deeply examine Grassmannian facts on their underlying Riemannian manifolds in an stop-to-give up getting to know structure. To perform discriminant gaining knowledge of on Grassmann manifolds, many works embed the Grassmannian into a Euclidean space. This may be finished both by way of tangent space approximation of the underlying manifold, or with the aid of exploiting a high-quality particular kernel function to embed the manifold into a reproducing kernel Hilbert space. In each of such cases, any present Euclidean method can then be carried out to the embedded information, considering that Hilbert spaces respect Euclidean geometry. For example, first embeds the Grassmannian into a high dimensional Hilbert area, and then applies conventional Fisher analysis approach. Obviously, most of those techniques are restricted to the Mercer kernels and consequently constrained to apply best kernel primarily based classifiers. Moreover, their computational complexity increases steeply with the range of education samples.

The Grassmann manifold G(m, D) is the set of m-dimensional linear subspaces of the R and D. The G(m, D) is a m(D−m)-dimensional compact Riemannian manifold.

An element of G(m, D) can be represented by an ortho normal matrix Y of size D by m such that Y = Im, where Im is the m by m identity matrix. For example, Y can be the m basis vectors of a set of pictures in R D.

However, the matrix representation of a point in G(m, D) is not unique: two matrices Y1 and Y2 are considered the same if and only if span(Y1) = span(Y2), where span(Y) represents the subspace spanned by the column vectors of Y . Equivalently, span(Y1) = span(Y2) if and only if Y1R1 = Y2R2 for some R1, R2 ∈ O(m). With this understanding, here will often use the notation Y when user actually mean its equivalence class span(Y), and use Y1 = Y2 when user mean span(Y1) = span(Y2), for simplicity.

Practically, the Riemannian distance is measured between two subspaces is the length of the shortest geodesic connecting the two points on the Grassmann manifold. However, there is a more intuitive and computationally efficient way of defining the distances using the principal angles.

Steps in Grassmann Algorithm

The Grassmann algorithm is a mathematical technique that is often used in face recognition to analyze and compare facial features. Here are the basic steps involved in using the Grassmann algorithm for face recognition:

- **Feature extraction:** The first step is to extract facial features from the images of the faces to be recognized. Commonly used techniques include Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

Face representation: Next, the extracted facial features are represented as points in a high-dimensional space. This space is often referred to as a feature space or a face space.

- **Grassmann manifold:** The Grassmann manifold is a mathematical space that represents all possible subspaces of a fixed dimension in a high-dimensional space. The Grassmann algorithm uses this manifold to compare the subspaces that represent the facial features of different faces.

Subspace projection: Each face is represented as a subspace in the feature space. The Grassmann algorithm then projects these subspaces onto the Grassmann manifold to create a set of points that can be compared.

- **Distance computation:** Finally, the distance between the subspaces is computed using a distance metric such as the Grassmann distance. The distance metric takes into account the geometry of the Grassmann manifold and provides a measure of how similar or dissimilar the subspaces are.
- **Classification:** The computed distances are then used to classify the faces into known or unknown individuals. This step typically involves setting a threshold value for the distance metric, above which a face is considered to be unknown.

Overall, the Grassmann algorithm is a powerful technique for face recognition that can handle variations in lighting, pose, and facial expressions. It is particularly useful when the number of training samples is small, as it can effectively capture the variability of facial features in a low-dimensional space.

IV. PROCEDURE

Enrolment Phase

Enrolment is the process of uploading student's information in server. The student enrolment module should allow capturing student information, including their names, student IDs, and other relevant details. Admin has the ability to add student information and make changes in student database. This module is responsible for managing user accounts and permissions. It allows administrators to create and delete user accounts, as well as assign roles and access levels. Admin has unique login id for verification. This ensures the confidentiality of student's information.

Face Image Register

In this module student face image is capture in real time. Use the Grassmann learning algorithm to train a model that can recognize the enrolled students' faces. Grassmann learning is a matrix-based approach that can handle high-dimensional data, making it suitable for face recognition. Facial features are extracted and registered for further process. To extract facial features using Grassmann learning, first need to represent the face images as points on the Grassmann manifold. This can be achieved by projecting the face images onto the subspace that represents the face images' variability. Then extract feature points using local binary pattern and histogram analysis methods. Train a classifier using the extracted features and a labeled dataset.

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Face Recognition

This module is responsible for identifying individual faces and matching them with known identities. It uses machine learning algorithms to create a unique digital signature for each face, which can then be compared against a database of known faces. Face recognition using Grassmann learning is a computationally intensive technique but has been shown to be effective in various applications. It is important to ensure that the dataset is large enough to build a reliable model and that the preprocessing steps are consistent to ensure accurate feature extraction. Student's current face image is capture in real time using web camera and extract the feature values from captured image. Then apply classification process to detect whether the student's face image was present or not.

Attendance Phase

This module is responsible for recording attendance data and generating reports. It typically integrates with other modules to retrieve data on when and where a face was detected, as well as the identity of the individual associated with that face. Once face image was verified, the system then proceeds to record the student's attendance. If the image does not match, the system marks the student as absent.

Alert System

This module is responsible for providing a user-friendly interface for administrators and users. It typically includes features such as real-time monitoring, reporting, and configuration settings. This application will automatically send attendance notification to the predefined contact numbers of the parents. Parents can know their children attendance details in class.

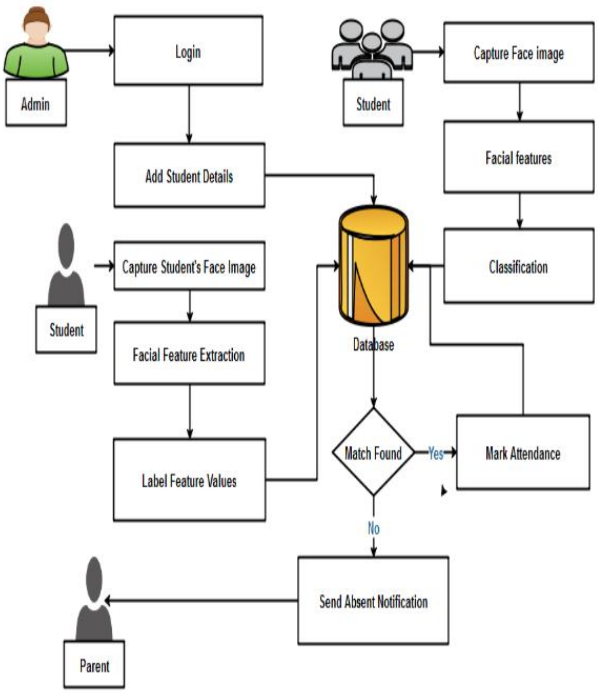

Fig 4.1: Architecture for Proposed Work

V. CONCLUSION

The face recognition based attendance system using Grassmann learning algorithm is a promising solution that can improve the accuracy and efficiency of attendance management. The use of Grassmann learning algorithm in face recognition based attendance system is an innovative and promising approach. The system can accurately recognize faces and use the data to manage attendance in a more efficient and convenient way. One of the benefits of using Grassmann learning algorithm is its ability to handle high-dimensional data and capture the intrinsic structure of the face data. This leads to better accuracy in recognition and reduces the chances of false positives and false negatives.

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