Automatic Bus Pass Verification System through AI

R. P. Kumawat[1], Samruddhi Deshmane[2], Mhase Aditi[3], Ohol Ashwini[4], Pathan Joya[5]

[1]*Professor, Dept. of Cloud Computing and Big Data, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India*

[2,3,4] *Final year Diploma Student, P.Dr.V.V.P. Institute of Technology and Engineering, Loni, Maharashtra, India*

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Abstract - Manual checking by bus conductors is the old method of verifying bus passes; this is labor-intensive and error-prone. It might also make it easier for unidentified people to travel without being checked. We propose an AI-powered Automatic Bus Pass Verification System to address these concerns.To automate the passenger verification process, the suggested solution employs deep learning and computer vision methods for facial identification. The system processes the acquired frames using OpenCV for face detection, utilizing a camera situated at the entrance of the bus to capture the passenger's face. After the faces have been identified, they are processed before being sent into a CNN model that has been trained with photos of people who have already registered.A database of registered bus pass holders is checked against the captured face by the system. The entry is logged with the date and time if a match is detected, and the passenger's bus pass is automatically checked. An unauthorized user is identified as a traveler whose face does not match the database. A database contains all verification data for administrative and monitoring reasons.Using this method in public or institutional transportation systems improves verification accuracy, lowers manual effort, and increases security.

Key Words: Automatic Bus Pass Verification, Artificial Intelligence, Face Recognition, Convolutional Neural Network (CNN), OpenCV, Computer Vision, Passenger Authentication.

1.INTRODUCTION

School buses, college buses, and city buses are all part of the public transportation system, which is vital since it allows people to move easily and cheaply. Bus passes enable customers to travel frequently without buying tickets every time. These passes are offered by various institutions and transportation agencies. Before letting a passenger board, the conductor or driver would usually manually verify their passes. But there are a few problems with manually checking bus passes. It might be laborious, wasteful, and prone to human mistake during busy times. Further, bus permits that are counterfeit, out-of-date, or otherwise misused can go undetected when checked manually, which can lead to inconvenient situations.

A lot of old manual systems are getting replaced by smart and automated ones because of how fast computer vision and Artificial Intelligence (AI) are developing. The capacity of face recognition systems to reliably identify people from photographs has made them a hot topic in recent years. Biometric authentication, access control, security surveillance, and attendance management are just a few of the many common uses for these systems. Bus pass verification is another area that could benefit from this technology's use to transportation systems.

Using face recognition technology, the Automatic Bus Pass Verification System is meant to automate the process of passenger identification and verification. One component of this system is a camera mounted at the bus's entry, which records still photos or video frames as riders board. In order to identify and remove the face from the photos, computer vision algorithms are applied to the collected data. The algorithm then compares the analyzed facial traits to a database of registered bus pass users using a Convolutional Neural Network (CNN) model.A dataset with pictures of permitted travelers is used to train the CNN model. As part of the authentication procedure, the trained model is fed a preprocessed picture of the subject's face and asked to identify whether or not they have a registered bus pass. The system will automatically verify the passenger's bus pass and record the entry with details like name, date, and time if it finds a match in the database. If no match is found, the passenger is tagged as an unauthorized user and their information can be saved for future inspection by the transit authority or the management of the institution.

The benefits of this automated technique over more conventional approaches to manual verification are numerous. Bus conductors have less work to do, boarding is faster, and passenger identification is more accurate. Also, by limiting bus rides to approved users exclusively, it helps stop people from abusing their passes. For administrative, analytical, and monitoring reasons, the system also keeps a digital record of passenger verification.

The application of AI-powered face recognition also enhances transportation management efficiency and safety. Using tools like OpenCV for face detection and CNN for facial feature identification, the system is able to execute highly accurate real-time verification. So, for contemporary transportation systems, especially in controlled transport settings and educational institutions, the suggested Automatic Bus Pass Verification System is an intelligent and trustworthy option. Bus pass verification may be made much more efficient, dependable, and secure with this system's installation, all while cutting down on operational delays and human labor.

[1] Philipp Terhörst et al. found that high-quality samples are the main driver of modern FR systems' outstanding performance. Determining the FIQ of a captured face, for example, in an automated border control scenario, ensures a good sample quality. Consequently, during enrollment, a captured face could be rejected without any indication of the quality reducing factor. The author of this paper put forth a technique for computing pixel-level quality explanation maps, which can help identify the most and least useful parts of a face for recognition. So, the suggested method gives you the lowdown on how useful a human-readable facial image is. In order to get the pixel-level quality maps for a face image, the author proposes a training-free method that, given any FR network, may be executed in three stages.

[2] in Real-Time Bus Tracking Mobile Application, created by Nagababu Garigipati et al., is an attempt to help students who use campus buses. With more and more students using their phones for schoolwork, it would be great if there was an app that could help them plan their commutes.

[3] The present number of surveillance cameras is too high for the hardworking employees at the Safety Management Centre to visually inspect, according to Hyun-Bin Kim et al. This leads to delays in the identification of criminals and the unnecessary disposal of a large amount of recorded film. It is challenging to demonstrate a direct preventative effect, since previous research with surveillance cameras has demonstrated that being aware of their existence can promote impulsive criminal action. It is also not possible to use the recorded photos for post-mortem investigations or real-time identification when using artificial intelligence to analyze them. Based on analysis of surveillance footage from installed cameras and the expansion of recorded data, this paper suggests a system that can identify potentially dangerous individuals in real-time. The system would also include an application that could verify a person's identity in real-time and notify public safety agencies of their identification.

An examination of earlier research that was deemed a Literature Survey is presented in the second part of this publication. Section 3 provides a comprehensive description of the proposed methodology, outlining the path of action. The experimental evaluation is covered in Part 4, possible modifications are discussed in Section 5, and the essay concludes with a conclusion on the existing plan.

2. LITERATURE SURVEY

[4] In an unstructured classroom setting, Nianfeng Li et al. investigated a dataset of Chinese students' faces. The author employs four face recognition models OpenFace, DeepFace, DeepID, and ArcFace on the UCEC-Face dataset and conducts experiments with four additional datasets AT&T, CASIA, CELEB, and MFace under identical circumstances in order to confirm the effect of facial images on the performance of face recognition models in an uncontrolled setting. author compare the outcomes.In author's dataset, there are more factors than in the previous four: subject age, illumination fluctuation, subject stance, subject expression, image size, subject facial occlusion, and angle of the photographed face, among others. At its peak, the OpenFace model achieved 74.2% accuracy on the facial recognition test with the AT&T dataset, 71.1% with CASIA, 75.9% with CELAB, 76.3% with MFace, and 56.0% with UECE-facial. Table 11: The UCEC-Face dataset and its test face recognition algorithms compared using various cosine distance detection algorithms. In Table 12 author can see the results of comparing several face recognition algorithms tested on the AT&T dataset using various detection strategies based on cosine distance. In Table 13, author can see how various face recognition algorithms tested on the CASIA dataset fare when compared using various detection strategies based on cosine distance.

[5] Researchers Dominador M. Acasamoso Jr. and colleagues conducted experiments on random face scanning and found that it was effective in identifying employees' faces. The software's face recognition capacity was able to identify registered personnel in all studies, regardless of skin tone, face shape, or distance from the camera.

[6] While Volodymyr Mykolaevich Opanasenko's mobile access control system relies on an accurate face recognition algorithm; it cannot provide foolproof identify verification on its own. Consequently, a mixture of many facial recognition algorithms should be employed as an ensemble if high dependability of such systems is required, particularly in essential applications, such as mobile devices. In this paper, this method is explored as a potential solution to the facial recognition problem. A key area for future research on ensemble face recognition methods is the extensive application of the algebraic theory of pattern recognition's mathematical tools. This theory provides a general framework for building correct algorithmic compositions using algebraic methods. In particular, the development of mobile devices to authenticate users when remotely accessing restricted-use information resources depends on the findings of these investigations. In particular, systems of active video surveillance of on-board systems benefit from this aspect of the defined system, which broadens its practical application.

[7] An enormous step forward in the development of user experience and public transportation administration was the Android Bus Pass System, which was proposed by Sayali Yadav et al. More efficient and user-friendly transportation services are the goal of the system, which uses mobile technology to simplify the process of getting, managing, and utilizing bus passes. Commuters and bus drivers alike will be satisfied with authors future bus pass system, which author are now working on creating an app for. The ability to establish various bus pass alternatives and update conductor profiles is within the administrative realm. Through the Android app that the user interacts with, the system will be able to generate QR codes. One of the most important features of this program is the implementation of safe online payment. Bus passes can be easily obtained online, saving users the trouble of standing in line. The system's main benefit is the decrease of paperwork. With this system implemented, issuing bus passes becomes a faster and easier process. Adding funds to an account and extending the validity of a pass is a breeze. Scanning a QR code gives bus conductors vital information about the person using the pass.

[8] In their comprehensive study, Joseph Thomas Año et al. explored the application of different convolutional neural networks in the detection of skin disorders. VGGNet, GoogLeNet, ResNet, DenseNet, ConvNeXt, and EfficientNet-v2 are just a few of the categorization networks that the author meticulously designs tests with. On the SD-128, SD-198, and SD-260 datasets, the author compares their own implementation with the most recent methods for skin disease

categorization. In comparison to prior techniques, the author's version of EfficientNet-v2 achieves classification accuracy of 66.83% on the SD-198 dataset, 65.40% on the SD-126 dataset, and 63.04% on the SD-260 dataset, according to the author's experiments. You can find the author's code and trained models online, so you can utilize them in real-world applications.

[9] Yu Sun et al. proposed addition to innovating teaching methods, optimizing teaching processes, and reforming curriculum assessments, teachers need to utilize information technology to monitor the academic quality of college students. This article explores and practices the monitoring of academic quality for students majoring in Big Data Management and Application at Guangdong University of Science and Technology, based on artificial intelligence technology. By using artificial intelligence for learning situation analysis, learning status correlation analysis, course warnings, learning status warnings, and other methods, students can gain a clear understanding of their own learning status. Simultaneously, teaching assistants can employ different monitoring methods based For universities, firmly grasping the task of talent training is key to gaining competitive advantages. In addition to innovating teaching methods, optimizing teaching processes, and reforming curriculum assessments, teachers need to utilize information technology to monitor the academic quality of college students.

[10] In order to identify early warning signals of chronic absenteeism among college students, Viktor Erdélyi et al. developed a screening tool and implemented a student support system. The author collaborated with psychiatrists to identify sleep issues and reduced student participation as significant signs. Instead of relying on supplementary equipment like wearables, the author distinguished this study by estimating these indicators using solely mass-produced cellphones, which are popular among college students.

[11] To preserve the person's identity while retrieving the best-matching bottom section of an occluded masked face image with a high SSIM value, Susanta Malakar et al. developed a technique. The author's approach makes use of an intricate algorithmic design. The author's method is noteworthy since it is publicly applicable and can process query photos that are not in any dataset, guaranteeing that the system is not pre-aware of the query image's visible region. At the outset, data is collected from open sources. The query image is used to enhance images from this collection, which are subsequently combined with the visible upper portion of the query image. For picture identification and categorization, the SURF method is used to determine the rotation. In order to assess the efficacy of the suggested method, author compare its SSIM, FID, and PSNR values to those of six standard approaches and measure the accuracy of recognition. Retrieving the lower section using the correct expression is the goal of future effort.

[12] The work of Lihua Yang et al. on the FaceNet algorithm has been validated in the area of face recognition, and an attendance management system for students' classes has been developed using this method. Automated face recognition, classroom check-in, efficient and reliable data administration, and random roll call are all capabilities of the system. But the trial also found that camera resolution and face size affect recognition accuracy. Hence, in order to enhance recognition performance, future research should focus on optimizing algorithms and hardware performance. Facial recognition technology is already having a significant impact in many industries, and it will continue to do so as algorithms and hardware get more optimized. Schools and parents will have access to more thorough and objective attendance data support as the intelligent student attendance management system evolves and improves, which will aid in raising the bar for instruction and encouraging kids' individual growth.

[13] By standardizing procedures for issuing, renewing, and managing bus passes, the system developed by Mr. Sundararaju.G et al. improves record accuracy and decreases administrative workload. The solution makes sure that administrators and commuters have a better experience by digitizing the handling of bus passes. By following a disciplined strategy, bus pass requests and renewals are processed and tracked properly, with fewer errors and more accessibility. Future enhancements could concentrate on improving digital request handling and adding more validation procedures to increase efficiency and security. Currently, the system needs pass requests to be sent offline. As a whole, the Bus Pass Management System is an efficient and dependable system that improves the quality of public transit and helps the transportation department run more smoothly.

[14] Virtual reality (VR) has the potential to revolutionize education, according to Roberto Daza et al., who argue that it will outperform conventional e-learning in terms of presence, interaction, and biometric monitoring. The SMARTe-VR platform enhances instructor capacities and paves the way for AI-driven breakthroughs with its full VR architecture, which includes tools like Auto QA, textbook development, and biometric monitoring. In order to advance AL models in VR and support research in IRT, KT, and MMLA, the SMARTe-VR dataset and its related problems provide a significant resource. With an emphasis on comprehending detection during learning, SMART models provide a strategy based on state-of-the-art IRT models. They lessen the dependence on response data, increase adaptability, and enable real-time modifications based on student states using facial biometrics. Although additional study is necessary to guarantee broader application, these methodologies confirmed the author's data set with an accuracy of 85%.

3. METHODOLOGY

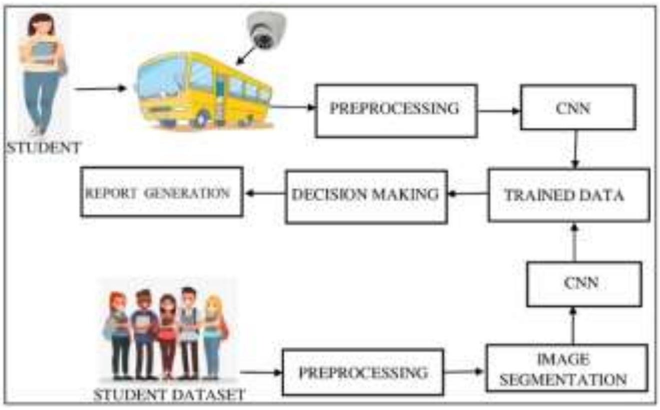

Fig 1: Overview Diagram

Below is the working process of the overview diagram of the proposed Automatic Bus Pass Verification System through AI. The system uses computer vision and deep learning techniques to automatically verify passengers' bus passes using facial recognition. The overall working process consists of several stages including frame capturing, image preprocessing, image segmentation, CNN-based feature extraction, and decision making for verification.

Step 1: Frame Capturing and Preprocessing

This is the first stage of the proposed system. In this stage, the system captures live video using a camera installed at the bus entrance. To enable real-time video processing, the OpenCV library is used. Once the camera is activated, the system continuously captures video frames from the live stream.

The captured frames are then processed using a Haar Cascade classifier to detect faces present in each frame. Haar Cascade uses predefined HAAR features stored in XML files to identify facial patterns within the images. When a face is detected, the detected region is cropped from the frame.

After face detection, the images are preprocessed to improve the performance of the AI model. Each detected face image is resized to 48 × 48 pixels with 3 color channels (RGB). Resizing ensures uniform image dimensions, which is necessary for training the neural network model.

The preprocessed images are temporarily stored in training and testing directories. These images represent the passengers who have valid bus passes and will be used later to train and test the verification system.

Step 2: Image Segmentation

In this stage, the captured images are prepared for training the AI model. Image segmentation helps in organizing and dividing the dataset into training and validation sets.

For this purpose, training and validation generators are used. The training generator processes the images by setting the target image size to 48 × 48, batch size to 32, and color mode to RGB. The class mode is set to categorical, which allows the system to classify images according to different registered passengers.

Similarly, a validation generator is created to evaluate the performance of the model during training. It also uses the same image size (48 × 48), batch size of 32, RGB color mode, and categorical class mode. This segmentation ensures that the model learns effectively from the training data while its performance is validated using unseen images.

Step 3: Convolutional Neural Network (CNN)

This is the core component of the proposed system. The Convolutional Neural Network (CNN) is responsible for identifying and verifying passengers based on their facial features. The CNN model receives the preprocessed images collected from the previous stages. These images are used to train the model to recognize different registered bus pass holders. The neural network is built using the Sequential class from the TensorFlow framework. Initially, a convolutional layer with 32 kernels of size 3 × 3 and the ReLU activation function is added. This layer processes images of size 48 × 48 and extracts important facial features.

Another convolution layer with 32 kernels of size 3 × 3 and ReLU activation is added to improve feature extraction. After this, a Max Pooling layer of size 2 × 2 is applied to reduce the dimensionality of the feature maps and improve computational efficiency. A Dropout layer with 25% regularization is used to prevent overfitting. Next, fully connected layers are added to the network. The feature maps are flattened, and a Dense layer with 100 neurons and ReLU activation is included to learn complex patterns in the facial features.

Finally, the output layer is created with multiple classes, where each class represents a registered passenger in the bus pass database. During training, the Adam optimizer is used to improve model accuracy, and the model is trained for 100 epochs. After training is completed, the trained model is saved in an H5 file, which stores the learned weights and parameters of the neural network. This trained model is later used for verification during real-time operation.

The equations 1 and 2 below display the ReLU and Sigmoid functions respectively.

$f(x) = max(0, x)$ ___ (1)

Where, x is any positive value

$S(X) = \frac{1}{(1+e^{-X})}$ ______(2)

Where,

X is the input to a neuron

$f(x) = Relu\ Activation\ Function$

$S(x) = Sigmoid\ Activation\ Function$

e= Euler's Number

Figure 2 depicts the architecture of the Convolutional Neural Network.

Layer	Activation
32 X 3 X 3 2D	Relu
MaxPooling2D	
32 X 3 X 3 2D	Relu
MaxPooling2D	
32 X 3 X 3 2D	Relu
MaxPooling2D	
Flatten	
Dense 100	Relu
Dense 1	Sigmoid
Adam Optimizer	

Figure 2: Architecture of Convolution Neural Network

Step 4: Decision Making and Bus Pass Verification

After the CNN model is successfully trained, the system moves to the decision-making stage. During real-time operation, the camera captures the passenger's face when they enter the bus.

The face is detected using Haar Cascade through OpenCV, and the detected face is cropped from the frame. The cropped image is then resized and processed before being passed to the trained CNN model.

For additional verification, skin detection can be performed using the YCbCr color model to identify skin regions in the detected image. This helps in improving the accuracy of face detection by separating skin pixels from the background.

The chrominance components (Cb and Cr) are calculated from the RGB pixel values using the following equations:

Cb=-0.169*R-0.332*G+0.500*B+128 --(3)

Cr=0.500*R-0.419*G-0.081*B+128-----(4)

Pixels that fall within the specified Cb and Cr ranges are classified as skin pixels. These pixels are converted to white, while the background pixels are converted to black, forming a binary image that highlights the facial region.

The processed image is then passed to the trained CNN model stored in the trained.h5 file. The model compares the detected face with the stored dataset and identifies whether the passenger has a valid registered bus pass.

If a match is found, the system automatically verifies the passenger's bus pass and records the passenger's name, date, and time of entry. If the face does not match any registered passenger, the system flags it as an unrecognized passenger.

All the verification records are stored in a database, which can be accessed by the transport or college administration to monitor bus pass usage and identify unauthorized passengers.

4.RESULTS AND DISUSSIONS

The proposed methodology for the Automatic Bus pass Verification System, which aims to apply the CNN technique, is a combination of Java and Python. Method development for the offered method was carried out using the Sypder and NetBeans IDEs. Among the development system's specifications were 8 GB of RAM, an Intel Core i5 processor, and 500 GB of storage. The person's face is captured using either the laptop's built-in webcam or an external picture capture source. The convolutional neural network is the main model that needs to be evaluated for proper student face identification. A performance review is necessary for finding any mistakes made when implementing the model. The assessment procedure is described below.

Evaluation of Performance Using the Root Mean Square Method

The system for Automatic Bus pass Verification utilizing convolutional neural networks has been the subject of several tests aimed at measuring its inaccuracy. Because of the mistake that the method for accurate facial recognition makes, analysing performance metrics is a breeze. The provided approach's error can be determined using the Root Mean Square Error (RMSE). The offered approach for face identification using CNN contains inaccuracies, which indicates that the proposed strategy performs accurately. By using the root-mean-squared (RMSE) method, evaluating the error between two continuously correlated parameters becomes much easier. Accuracy and inaccuracy in face identification are the main parameters taken into consideration by this method. The assessment of this data is followed by the calculation of the error using equation 5.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{1,i} - x_{2,i})^2}{n}} \quad \_\ (5)$$

Were,

$\sum$ - Summation

(x1 – x2)2 - Differences Squared for the summation in between the expected No. of face identifications and the obtained No. of face identifications

n - Number of Trails

These two variables are measured using ten distinct users who each complete ten trials on the system using different facial expressions. The trial results are recorded in table 1, which is provided below.

User no	No of Expected Face Identification	No of obtained Face Identification	MSE
1	10	8	4
2	10	9	1
3	10	7	9
4	10	10	0
5	10	10	0
6	10	7	9
7	10	8	4
8	10	9	1
9	10	9	1
10	10	10	0

Table 1: Mean Square error measurement

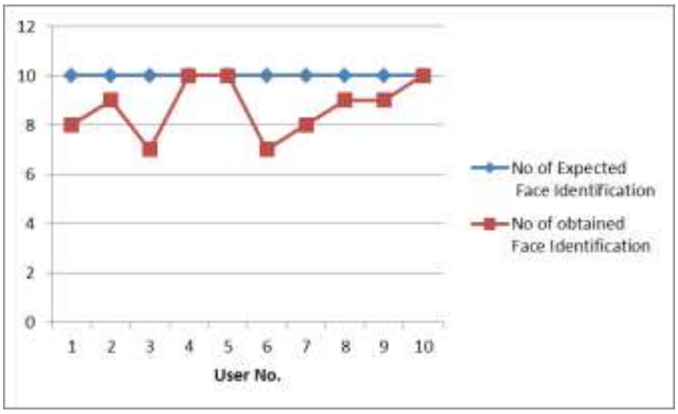

Figure 3: Comparison of MSE in between Expected No of face identifications V/s obtained No of face identifications

The graphical representation of the error rate provided by figure 3 above has been made easier by the results of the experimental evaluation of the method. The graph shows the least amount of inaccuracy the algorithm encountered when interpreting users' looks to determine their face. This is explained by the Convolutional Neural Network's extremely accurate implementation, which significantly increases detection accuracy. The results are also improved by the decision-making method, as evidenced by the MSE and RMSE values of 2.9 and 1.702, respectively. This assessment shows how precisely and accurately the facial recognition method was developed for passenger evaluation in bus.

5. CONCLUSIONS

The proposed system effectively demonstrates the use of deep learning techniques, particularly Convolutional Neural Networks (CNN), for automated student monitoring and analysis. By integrating image acquisition through cameras, preprocessing, image segmentation, and trained CNN models, the system is able to extract meaningful features from student data and support accurate decision making. The trained dataset enhances the reliability of predictions, while the report generation module provides clear and structured outputs for further evaluation. Overall, the system reduces manual effort, improves accuracy, and offers a scalable solution for intelligent monitoring in educational environments. In the future, the system can be enhanced by incorporating real-time video analytics and advanced deep learning models to improve accuracy and performance. The framework can be extended to handle larger datasets and multiple cameras for wide-area monitoring. Integration with cloud platforms and IoT devices can enable remote access, scalability, and real-time alerts. Additionally, the system can be adapted for applications such as attendance automation, behavior analysis, and safety monitoring in smart campuses.

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