Automatic Number Plate Recognition and Theft Detection System for Android-Based Platforms

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***Abstract*—One of the most significant uses of artificial vision systems nowadays is the automatic detection and recognition of automobile license plates. Car plates are not the best way to identify a car because they can be altered, stolen, or simply messed with. The goal is to create a system that takes a digital picture of a vehicle's identification number (VIN) or chassis number and then uses the characters from the embossed VIN to identify the vehicle electronically. This paper introduces a new algorithm for identifying vehicle chassis numbers that uses artificial neural networks and optical character recognition (OCR). More than a thousand car photos with various levels of ambient light are used to test the system. The angle of view and distance from the vehicle changed depending on the experimental setup, yet the VIN remained in focus throughout taking these pictures. Several common image processing methods were used in the pre-processing of these photos. The suggested OCR system was then fed the resulting photos. A three-layer artificial neural network (ANN) with topology 504-600-10 makes up the OCR system. This work's main accomplishment is the 95.49% true identification rate with zero erroneous identification. Lastly, look for any differences between the mobile number in the database from the two photos and the location associated with the mobile number from the VIN number database.**

***Index Terms*—vehicle identification number (VIN), optical character recognition (OCR), artificial neural network (ANN).**

I. INTRODUCTION

Every automobile made has a unique identifying number called the Vehicle identifying Number (VIN), sometimes referred to as the chassis number. The VIN remains the same for the duration of the vehicle's life, although the registration number is subject to change. Furthermore, since the registration number can be transferred to another vehicle, it is not specific to one vehicle. Depending on the car's make and model, the chassis number is usually located on the body frame, near the engine. The engine compartment and the dashboard of the car are separated by the firewall behind the motor. Almost always, the chassis number is located in the centre, at the top of the firewall, and is either stamped on a silver "credit card"-sized plate or in the same colour as the paintwork. Unlike the VIN, the license plates can be purposefully changed in fraud circumstances or replaced (for example, with a stolen plate). Applications for optical character recognition (OCR) are numerous and vary from transforming anything that can be read by humans to creating representations that can be altered by machines. The conversion of optically scanned bitmaps of written or printed text characters into character codes like ASCII is known as optical character recognition, or OCR. The goal of OCR is to make it possible for computers to recognise optical symbols without the need for human assistance. Finding a match between the features taken from the symbol's picture and a library of image models is how this is done. Computer systems that include such an OCR system enable compact storage, quick retrieval, and other file manipulations, as well as speed up input operations and reduce human error.

II. LITERATURE SURVEY

Every mentoring program is built on top of Performance Analysis Systems. Without a doubt, a person will progress with the guidance and assistance of statistical data, which will also help the business where he works succeed. A background inquiry is carried out in order to look at similar contemporary approaches that are utilised to analyse student performance. Before starting our literature research, we first learn about three existing systems that are comparable to the suggested system.

Unlike license plate recognition, the VIN identification method is new and more difficult. This is because VIN numbers vary depending on the make and model of the car, but license plates have a set format (at least) throughout regions. Additionally, the license plates have a uniform, noticeable appearance with a sharp contrast between the foreground and background, which makes character separation quite simple. However, it is challenging to discern because the VIN is stamped on the automobile body. After locating the license plate in the picture, many methods have been devised to segment each character, including Markov random fields (MRFs) [6], mathematical morphology, and feature vector extraction [5].

Although the approach is too computationally difficult to be offered for real-time license plate identification, the work in [5] suggests that the method might be employed for character segmentation in plates with indistinguishable characters during offline operation. The technique in [5] was created for the purpose of segmenting license plates in video clips. Nevertheless, automated character recognition was not a good fit for the segmentation findings. Many techniques, mostly used in optical character recognition applications, used hidden Markov models (HMMs) [7][8], Hausdorff distance [9], SVM-based character recognisers [10], and template matching [11][12] to recognise segmented characters. The approach in [8] highlights the need for strong character analysis when putting HMM into practice, which limits the recognition system's effective distance. The primary issue with Hausdorff distance is that, although having a recognition rate that is comparable to that of neural-network classifiers, it is slower. Therefore, if real-time needs are not particularly tight, it works well as a supplementary technique. If more time is available, it can be utilised to enhance another classifier's findings [9]. A system using four Support Vector Machines (SVMs) was created by the authors of [10], who report an exceptional average character identification rate of 97.2%. However, because the architecture is specifically made for Korean license plates, it cannot be used with license plates from other nations. Furthermore, a number of neural-network designs have been designed for the purpose of identifying number plates [13][14], but none of them have been tested or utilised with the VIN.

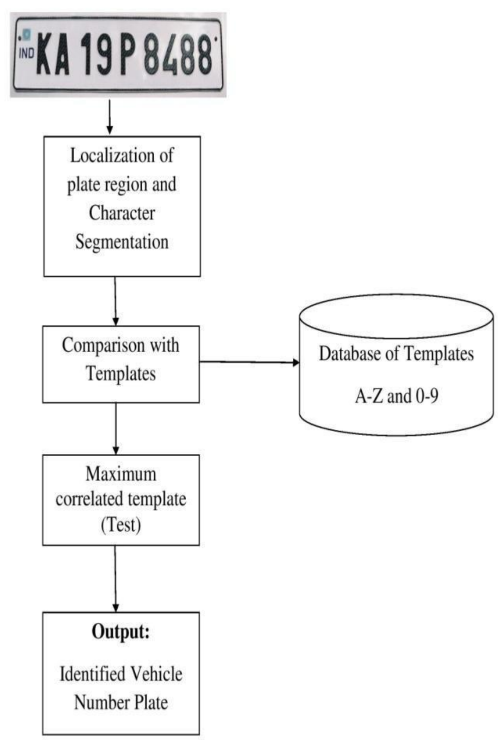
III. SYSTEM IMPLEMENTATION

Existing System

Unlike license plate recognition, the VIN identification method is new and more difficult. This is because VIN numbers vary depending on the make and model of the car, but license plates have a set format (at least) throughout regions. Additionally, the license plates have a uniform, noticeable appearance with a sharp contrast between the foreground and background, which makes character separation quite simple. However, it is challenging to discern because the VIN is stamped on the automobile body. After locating the license plate in the picture, many methods have been developed to segment each character, including Markov random fields (MRFs), mathematical morphology, and feature vector extraction.

Proposed System

The initial step in optical character recognition (OCR) is image acquisition. A CCD (Charged Coupled Device) camera is used to take an image of the numerical code that was punched on the machine casting. Plotting a histogram of around 100 pictures from the collection of roughly 1,000 chassis numbers was the first step.



Proposed Architecture

Data concentration is significantly higher in the upper few grey levels of the histogram, according to the histograms. It is impossible to establish a static global threshold since there may be some information loss in the pictures due to variations in the VIN size and the degree of chalking of the punched codes. Preprocessing is thus necessary before using the OCR method.

Methodology

Sign in

You benefit from the administration module: Integrate First Search with your services and adapt it to the demands of your users and authorised personnel.

Verification

A plug-in that gathers user data, including a password and user ID, and compares it to database records is called an authentication module. A realm can have more than one Active Directory authentication configuration defined.

Edge detection

Horizontal and vertical edge detection make up the first preprocessing algorithm module. To recognise the characters on the chassis, edge detection is essentially necessary. Since the VIN varies depending on the vehicle's manufacture, this is a crucial step. Because Sobel kernels are made to react as best they can to edges that run both vertically and horizontally with respect to the pixel grid—one kernel for each of the two perpendicular orientations—a Sobel mask is utilised. As seen in Figures 1(b), 1(c), 2(b), and 2(c), the mask is applied independently to the input picture to generate distinct measurements of the gradient component in each direction (Gx and Gy). As seen in Figures 1(d) and 2(d), these are then added together to get the gradient's absolute magnitude at each location. The formula for the gradient magnitude is mod G = qG2 x + G2 y - (1).

Edge detection is followed by thinning, normalisation, and segmentation.

Box detection

The chassis number is first horizontally segmented off of the visual backdrop in this module. As seen in Figures 1(e) and 2(e), we do this by scanning the image row-wise once from top to bottom and again from bottom to top. We then reject every row until we find one with a few white pixels. The backdrop has an intensity value of 0 (black), whereas the pixels that depict the chassis number characters have an intensity value of 255 (white).

Segmentation

For vertical segmentation, which involves column-wise scanning, a similar procedure is used. The spaces between the chassis code's rectangular boxes include the column with entirely black pixels. In order to determine these areas, we divide each character of the chassis number such that each one is divided into rectangular boxes, as seen in Figures 1(f) and 2(f).

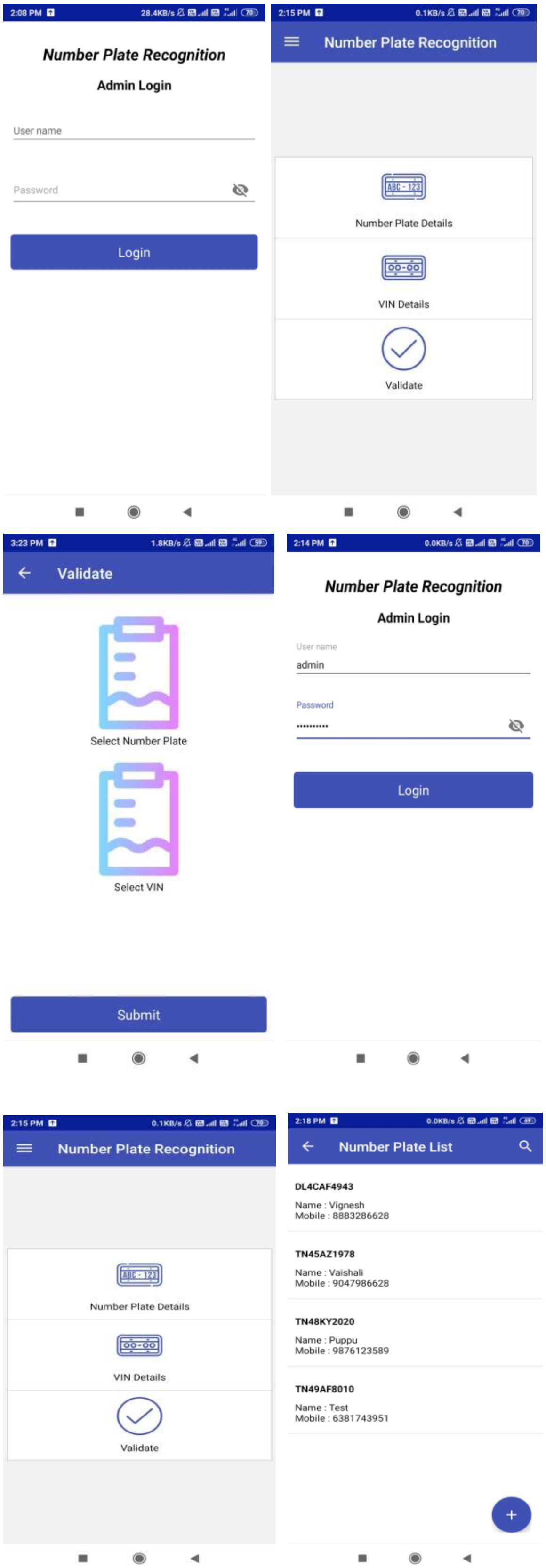
Template checking

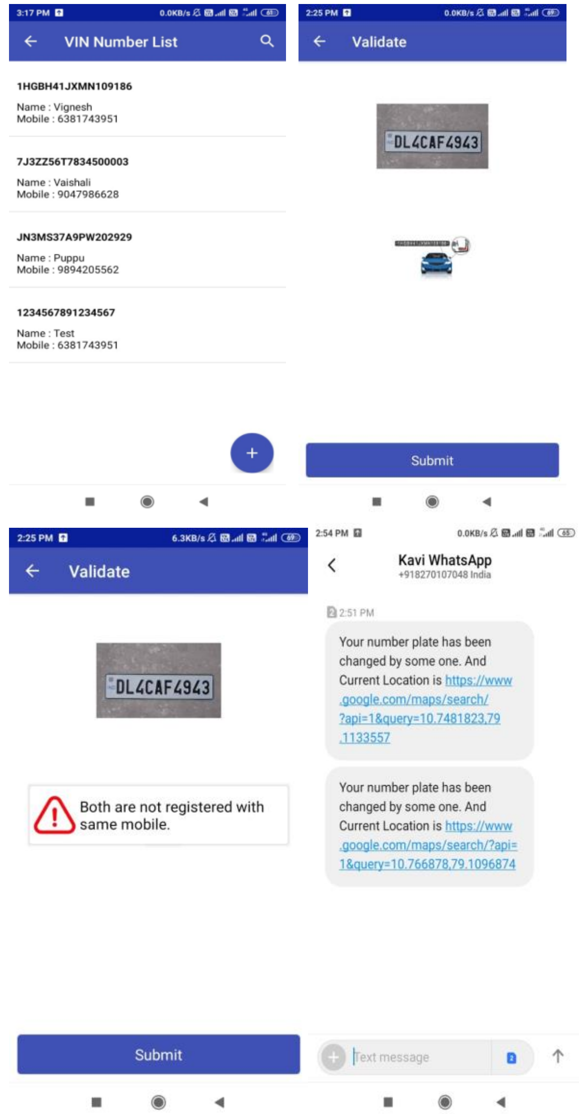
We use scaling to normalise the segmented characters of the chassis numbers to a fixed pixel size because they are in rectangular boxes of varying sizes. On the normalised photos, the rectangular boxes are then eliminated by deleting a small number of rows and columns that run along the box's edge. A study of hundreds of these photos was used to determine how many rows and columns need be removed in order to remove the box without changing the character. Therefore, after the box is removed, we are left with just the individual characters. which, as shown in Figures 1(g) and 2(g), must be thinned in the following step. 4) Thinning: As seen in Figures 1(h) and 2(h), morphological thinning is applied to individual images to reduce characters to a single pixel thickness while maintaining the whole length of those lines (i.e., pixels at the extreme ends of the lines should not be altered). A feed forward back propagation artificial neural network is currently used to identify and train these characteristics.

Location sharing

Users may share their position within a map view of your venue using the position-Based Services module. In addition to helping staff locate clients who want assistance, this tool can boost user social interaction. By establishing user groups and turning on location sharing, users may exchange and see one other's whereabouts in real time. Adding a position-Based Services module to your app will allow users to share their position and navigate the entire facility indoors.

Experimental Results





IV. CONCLUSIONS

The procedure came to the conclusion that an OCR-based artificial neural network-based chassis number recognition method is ideally suited for intelligent automotive systems. The main accomplishments of the suggested approach are that it yields zero mistaken identification rate (WIR) and a remarkably high number for correct identification rate (CIR). This is essential since even one erroneous VIN identification might result in inaccurate interpretations, such as location sharing to a cellphone number from the VIN number database. Automatic Number Plate Recognition (ANPR) systems have evolved from complex, costly, fixed-based applications that were difficult to set up to straightforward mobile ones that may employ the "point to shoot" technique thanks to modern technological advancements. This is made feasible by the development of software that operates on less expensive PCs and non-specialized hardware, eliminating the requirement for predetermined directions, angles, speeds, and sizes for the plate that would be passing inside the camera's field of vision. Along with smaller, more robust processors that fit in police cars, smaller cameras that can scan license plates quickly have also made it possible for law enforcement to patrol every day with the advantage of real-time license plate identification.

The automatic vehicle identification technology is expected to play a significant role in identifying defensive threats in the future.

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