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Original Article

Real-Time Somali License Plate Recognition Using Deep Learning Model

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Abstract - *The need for automatic license plate recognition is what is primarily driving the growing integration of computer technology in crucial industries like public transportation, healthcare parking, and retail parking. As cities grow, the interplay between technology and human needs becomes more obvious. In light of this trend, this paper presents a novel approach to license plate recognition in IoT-enabled smart parking systems, leveraging deep learning techniques. Traditional parking management systems often rely on manual monitoring or physical sensors, leading to inefficiencies and delays. In contrast, our proposed deep learning-based approach utilizes Convolutional Neural Networks (CNNs) for accurate license plate segmentation and character recognition. We curated a diverse dataset of Somali license plate images captured under various environmental conditions to train and evaluate our model. Through extensive experimentation, our model achieved an impressive accuracy rate of 96.76% after 80 epochs of training. Therefore, this research contributes to the advancement of efficient and accurate license plate recognition systems, facilitating enhanced parking management, traffic regulation, and urban mobility in smart cities.*

Keywords - *License plate detection, Deep learning, Somalian plate, Number plate recognition, Convolutional Neural Network.*

1. Introduction

It is well known that increasing urbanization has created a pressing need for transportation systems that are both efficient and intelligent [1]. Smart parking systems are a crucial part of this infrastructure, and their purpose is to address the difficulties related to urban parking by providing up-to-date information, maximizing the usage of parking space, and improving the overall user experience [2]. Meanwhile, in the context of intelligent parking system infrastructures, the detection and interpretation of license plates hold paramount significance. Techniques from the domain of computer vision are used to extract and decipher the information from license plates within images or video streams. The integration of such License Plate Detection (LPD) technologies into smart parking solutions facilitates the automatic regulation of vehicle entry and exit, streamlines the transaction process, and bolsters security measures. By superseding manual checks and the traditional issuance of physical parking slips, this technological fusion expedites the parking workflow and minimizes the necessity for human intervention. Consequently, LPD is a cornerstone technology for ensuring efficient and secured parking management within the sophisticated ecosystem of smart urban environments [3]. On the other hand, in the domain of IoT-enabled intelligent parking infrastructures, the role of video analytics is pivotal. Where conventional parking systems often depend on rudimentary machine learning methods or even manual monitoring, these can be inefficient and lack adaptability, especially when confronted with challenges such as variable lighting, obstructions, or non-standard license plate designs [4]. VA, on the other hand, harness the power of camera systems coupled with advanced computer vision techniques to gather and interpret visual information in real time. This approach facilitates continuous monitoring and astute analysis, providing a wealth of information about parking space usage, the length of stay, and instances of non-compliance. These technological advancements not only streamline parking operations but also elevate the user experience for motorists. Additionally, incorporating video data analytics into existing IoT frameworks empowers urban planners with a rich dataset for strategic decision-making, thereby optimizing the utilization of parking areas in the fabric of smart urban landscapes [5]. In the field of automated LPR, various strategies have been developed, with contemporary studies increasingly focusing on deep learning paradigms [6]. The fascination of deep learning lies in its proficiency in extracting complex patterns from large volumes of data. This approach diverges markedly from traditional techniques that depend on hand-engineered features and deterministic algorithms [7]. Deep learning algorithms, including

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innovative models such as the 'You Only Look Once' (YOLO) system for recognizing unclear plates, along with systems using CNNs, RNNs, and SVMs, have shown superior performance in discerning license plate information. The surge in available annotated datasets, coupled with breakthroughs in computational power, has spurred the adoption of deep learning within this field, inviting a wave of research into new methods and frameworks that promise to refine the efficacy of license plate recognition systems [8]. As an example, author [9] introduced a CIS transformer weight-sharing classifier that has the ability to identify every instance of a character regardless of its position. In recent years, researchers have done small cross-dataset studies to assess the applicability of the proposed methodology by the author [9] since the identification rates utilizing the traditional split methodology have significantly increased. Meanwhile, the CCPD is used to train their Chinese license plate recognition algorithms and it has shown a good result. Another author [10] has proposed a model that integrates optical character Mercosur license plates with real-world photographs, including various license plate designs. The results of a model-trained only on synthetic photos were promising. However, it is not feasible to accurately assess these results since the test images were not made available to the scientific community.

Even as deep learning advances the capabilities of license plate recognition systems across various languages, certain challenges and research opportunities remain. Balancing computational speed with precision remains a pivotal issue. The necessity for real-time video analysis demands that models operate with minimal computational load yet maintain a high degree of accuracy in identifying license plates. The body of existing research acknowledges these limitations, indicating a clear need for further innovation. Developing more streamlined deep learning models and enhancing YOLO (You Only Look Once) frameworks could offer solutions. These approaches are anticipated to provide an optimal compromise, enhancing processing speed without compromising the accuracy essential for effective LPR systems.

Therefore, this paper aims to explore the paradigm shift brought about by DL way that can be recognized LP, particularly within the context of IoT-enabled smart parking systems. By examining the technical foundations of DL architecture, specifically focusing on Convolutional Neural Networks (CNNs), we will elucidate their efficacy in handling the intricacies of license plate recognition tasks. Furthermore, we will discuss the integration of DL-LPR systems with IoT infrastructure, elucidating how interconnected devices, sensors, and cloud computing synergize to create a cohesive parking ecosystem. The significance of DL-LPR in smart parking systems extends beyond mere automation of entry and exit processes. It facilitates advanced functionalities such as vehicle tracking, payment automation, and enforcement of parking regulations with unparalleled accuracy and efficiency. Moreover, the scalability and adaptability of DL models allow for seamless integration with existing infrastructure, ensuring compatibility across diverse environments and deployment scenarios.

The primary research contributions of this study, tailored for implementation in Somalia's context, are outlined as follows:

1) Development of a Customized Dataset: This dataset will encompass diverse variations in plate formats, characters, and environmental conditions commonly encountered in Somali parking environments.
2) Designing a Cost-Effective and Accurate Solution: Formulating a deep-learning-based approach for LPR that aligns with Somalia's infrastructure constraints and technological capabilities. Emphasis will be placed on achieving a balance between computational efficiency and recognition accuracy, ensuring that the proposed system remains viable and accessible in Somalia's context.
3) Evaluation and Validation: Showing comprehensive experimental evaluations and performance assessments in real-world Somali parking environments. The efficacy and efficiency of the proposed methodologies will be rigorously tested to validate their suitability for practical deployment in Somalia.

By tailoring our approach to the specific needs and challenges of Somalia's parking management systems, this study aims to contribute towards the development of locally relevant and effective solutions for license plate recognition. The structure of this paper is organized as follows: Section 2 reviews related research studies. Section 3 details the proposed methodology for implementation. Section 4 presents the results of the methodology. Finally, Section 5 offers conclusions and discusses future work.

2. Related Word

LPR plays a crucial role in the field of intelligent transportation systems, particularly in the context of IoT-enabled smart-parking systems, as mentioned before. Over the years, significant advancements have been made in the field of LPR, with researchers continuously exploring novel methodologies to improve accuracy, efficiency, and robustness [11]. One of the works in LPR is the framework that author [12] introduced, which is Convolutional Neural Networks (CNNs) for character recognition tasks. Since then, deep learning-based approaches have dominated the field, showcasing superior performance compared to traditional methods. For instance, author [13] came up with a method for LPD and recognition using a combination of deep CNNs and other machine learning models. Their approach achieved remarkable accuracy, demonstrating the efficacy of deep learning techniques. In recent years, many scholars have used lightweight deep learning models for LPR, particularly to address the computational constraints of IoT devices. Author

[14] proposed a YOLO-based algorithm for license plate detection, which significantly reduced computational overhead while maintaining high-accuracy rates. Similarly, the author [15] developed a lightweight deep-learning model specifically tailored for license plate recognition in resource-constrained environments. Their approach leveraged transfer learning and feature compression techniques to achieve impressive results with minimal computational resources. Furthermore, the availability of large-scale labeled datasets has been instrumental in advancing LPR research. The Chinese City Parking Dataset (CCPD), introduced by [9], has become a benchmark dataset for evaluating LPR algorithms, particularly for Chinese license plates. Similarly, other researchers have curated custom datasets tailored to specific regions or countries, such as the Mercosur dataset for Latin American license plates [16].

At the forefront of innovating parking management, the author [17] has pioneered a smart parking system that integrates machine vision with IoT technology. The system's design, utilizing camera-based imagery to monitor parking spaces, enhances real-time management. The inclusion of IoT bridges parking sensors and cameras with a central server, streamlining communication. Users benefit from a mobile app that provides instant access to parking availability, significantly diminishing the hassle of locating vacant spots. Nevertheless, the research predominantly concentrates on the technical construct while giving limited attention to the practical deployment considerations and scalability in diverse environments. Prospective studies could provide deeper insights into the real-world applicability and constraints of this smart parking solution.

In a similar vein, author [18] has proposed a system that harnesses IoT alongside machine learning algorithms to refine parking space management. The fusion of data from IoT sensors with predictive algorithms underpins a framework that optimizes parking space allocation. While users interact with this system through a mobile app for spot reservations, the research does not thoroughly address its real-world performance, leaving room for future studies to investigate its scalability and robustness across varied environments.

Moreover, the author [19] contributes to the discussion with an IoT-based intelligent parking model that focuses on maximizing the use of underutilized spaces. This model, supported by real-time updates to mobile and web applications, aims to inform users about open parking spaces, thereby promoting efficient space usage. Despite its user-centric approach, the study lacks empirical evidence from real-world testing, which is crucial for ascertaining its effectiveness. Future investigations are warranted to thoroughly assess the system's reliability and scalability, confirming its utility in different parking contexts. Meanwhile, the author [20] came up with a smart parking system utilizing image processing techniques to optimize parking space management as well. The system relies on image processing techniques to identify vacant spots, providing users with instant data on space availability through an accessible digital platform. Despite its innovative approach, the research does not address how the system fares under adverse lighting or during peak parking times, which could compromise the precision of the image processing. Simultaneously, [21] has embarked on enhancing Automatic License Plate Recognition (ALPR) by integrating deep learning algorithms. The goal was to craft an ALPR system characterized by both high accuracy and operational efficiency.

Although the results are encouraging, the study falls short of thoroughly examining how the system performs in less-than-ideal conditions, such as variable lighting, adverse weather, or irregular license plate configurations. Future endeavors could include rigorous testing in diverse settings to solidify the system's reliability and viability for real-world application. Reflecting on these explorations in IoT-enhanced smart parking solutions, a shared research imperative emerges: to refine the real-time detection of parking availability while also economizing computational resources.

Even with significant strides in the management of parking systems, there remains an observable gap in extensive real-world performance evaluation. To bridge this divide, forthcoming studies ought to pivot towards creating smart parking models that reconcile precision with computational efficiency. Systematic real-world testing and detailed assessments will be pivotal in propelling the sector forward, ensuring that these innovations can be effectively deployed in varied urban contexts. This is the underlying motivation for the present research proposition.

3. Proposed Model

This section presents the proposed DP approach for LPR using CNN. It will describe how the CNN model was designed, trained, and evaluated for accurate and efficient license plate identification. The technique includes data collection, pre-processing, model architecture design, training, validation, data augmentation, post-processing, recognition, and evaluation metrics. Figure 1 provides a detailed overview of the steps involved in implementing the proposed methodology, laying the foundation for the subsequent discussion.

Phase 1 is to do data acquisition and pre-processing. The methodology starts with the crucial step of acquiring a comprehensive dataset encompassing a wide array of LP images that have been captured under difficult environmental conditions for Somali Plates. These conditions include varying lighting conditions, angles, distances, and perspectives, mirroring the real world. The dataset's diversity ensures the CNN model's ability to generalize effectively across different situations.

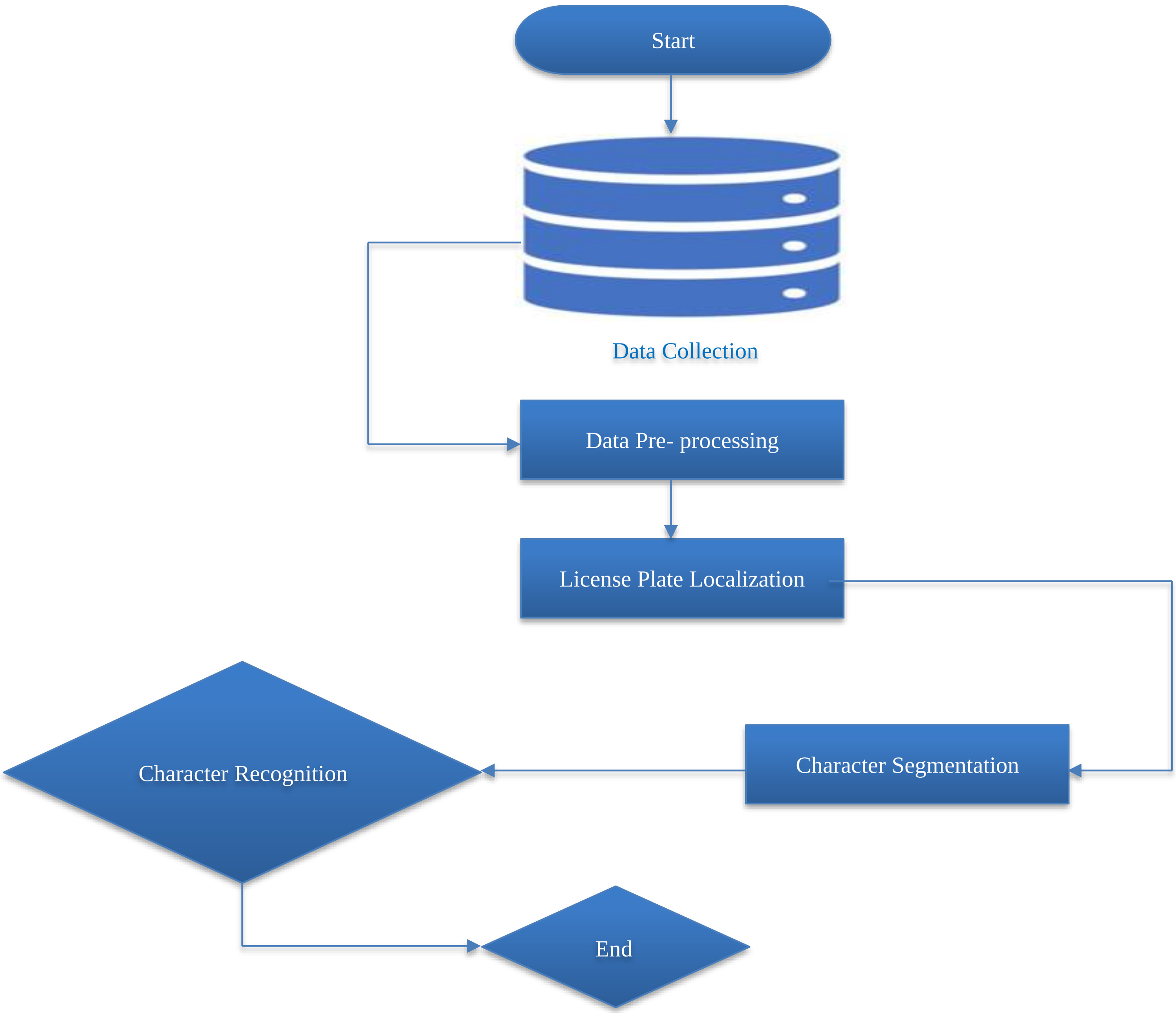

Fig. 1 Proposed methodology flowchart

Once the dataset was collected, pre-processing techniques were applied to standardize and improve the quality of the acquired pictures that will be used for training. Resizing the picture to a uniform size facilitates consistent input dimensions for the CNN model, enabling seamless integration during the training and inference phases. Additionally, normalization techniques are applied to adjust pixel values, ensuring uniformity and reducing the impact of varying illumination conditions. Furthermore, noise reduction methods are implemented to enhance the clarity and fidelity of the license plate images. We also applied median filtering to suppress noise and unwanted artifacts, thereby improving the overall quality of the dataset.

Phase 2 is Licence Plate Localization. Following pre-processing, the standardized images undergo license plate localization. License plate localization, an integral component of LPR systems, plays an important role in identifying and isolating the region containing the license plate within an image. Initially, ODT such as YOLO, SSD, or Faster R-CNN are applied to detect potential regions of interest (ROIs) within the image, marking them with bounding boxes. Subsequently, post-processing steps are used to filter out false positives and refine the localization results by considering criteria like aspect ratio, size, and shape characteristics.

Following this, region verification techniques are used to validate the accuracy of the localized regions by analysing additional contextual information. Once verified, the final output of the localization process is a precise bounding box or mask delineating the boundaries of the license plate region within the image. This localized region serves as input for subsequent stages of the license plate recognition pipeline, facilitating accurate character segmentation and recognition.

Phase 3 is Character Segmentation; following the detection of license plate localization regions, the process of character segmentation is initiated. This step involves identifying individual character contours within the detected license plate regions using contour analysis techniques. Character contours are extracted from the detected license plate regions using contour extraction algorithms available in the OpenCV library. Each contour represents a distinct character within the license plate region. These contours are subsequently resized to a standardized size to ensure uniformity across all characters for consistent processing. Hence, the resizing process involves adjusting the dimensions of each character contour to conform to a predefined size, typically determined based on the requirements of the subsequent recognition algorithm. Standardizing the size of each character contour facilitates uniformity in FE and recognition, thereby enhancing the accuracy of the overall recognition and the upcoming equation (1) is used to do the character segmentation.

$$E(x) = \sum_{p \in \beta} Up \times xp + \sum_{\{p,q\} gs} Vpq \times |xp - xq|, \quad xp c\{0,1\} \quad (1)$$

In the equation, β represents an image composed of a collection of pixels denoted by p within the set β. Each pixel p in the image is assigned a label xp, which can take the value of 1 or 0 to indicate whether the pixel is part of the foreground or the background, respectively. In this context, adjacent pixels are considered in pairs, and the terms "unary potentials" and "pairwise potentials" refer to Up and Vpq, respectively. Unary potentials pertain to individual pixels, likely reflecting how likely a pixel is to be foreground or background. In contrast, pairwise potentials refer to the relationship between a pair of adjacent pixels.

Phase 4 is the model architecture. In this phase, we focus on the architecture of the proposed model for character recognition, which utilizes a Convolutional Neural Network (CNN) framework. This design incorporates several convolutional layers, max-pooling layers, and fully connected layers, culminating in a softmax output layer responsible for classifying characters. The convolutional layers play a critical role in extracting essential features from the input images identifying spatial patterns and structures that correspond to different characters in the license plate images. After the convolutional layers, the generated feature maps are transformed into a one-dimensional vector, which is then passed through the fully connected layers. These layers refine the extracted features, allowing the model to learn more complex representations of the input data. Finally, the softmax layer outputs a probability distribution for each character class, allowing the model to predict the most likely character. Figure 2 illustrates the structure of the CNN model.

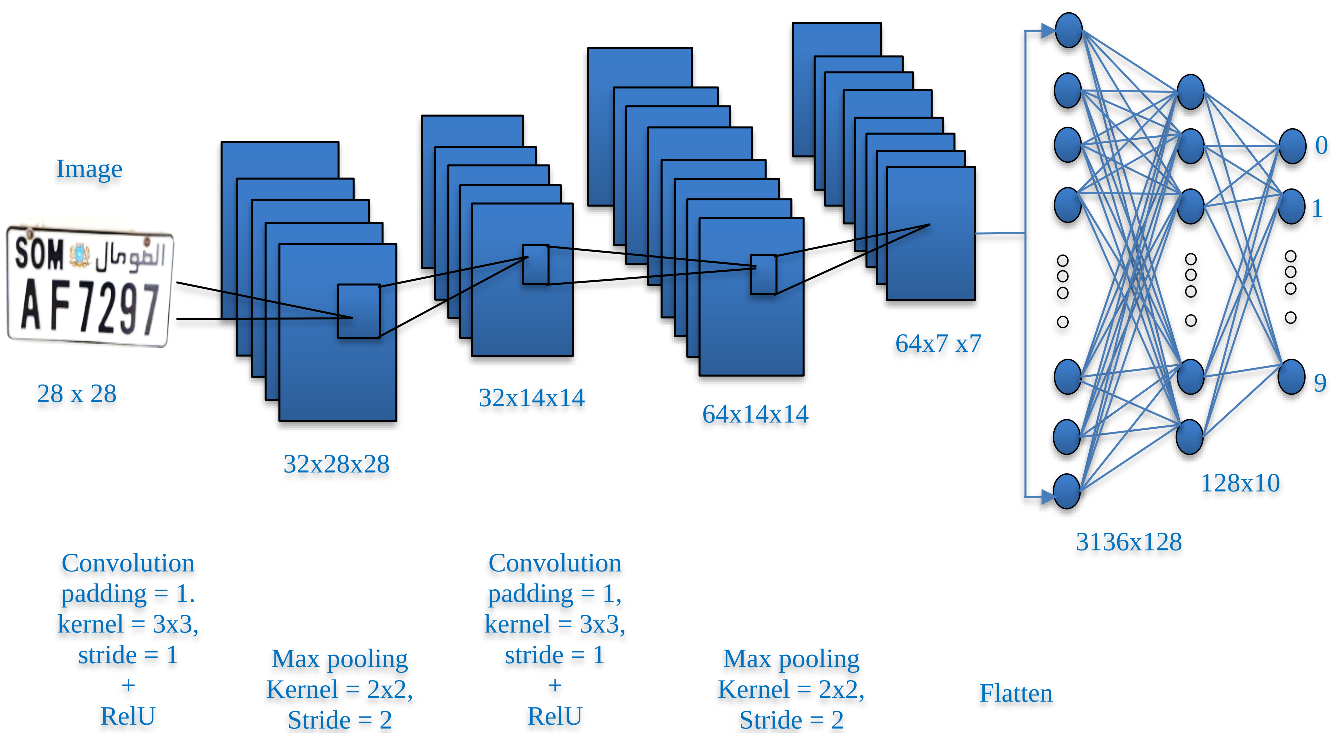

Fig. 2 Proposed CNN architecture

From Figure 2, the first thing is the Input Image: The network takes an input image, which in this case is resized to a fixed dimension of 28x28 pixels. This resizing is standard practice to ensure consistency in input data size for the CNN.

- First Convolutional Layer: The image is passed through a convolutional layer with padding set to 1, using a 3x3 kernel (filter) and a stride of 1.
- First Max Pooling-Layer: The output from the preceding convolutional layer undergoes downsampling through max pooling, using a 2x2 kernel with a stride of 2. This process reduces the spatial dimensions (width and height) of the feature map by half, resulting in a 14x14 size while preserving the most critical information from the original feature map.
- Second Convolutional Layer: Another convolutional layer follows, again with padding of 1, a 3x3 kernel, and a stride of 1, followed by a ReLU activation function. These further process the data to extract more complex features.
- Second Max Pooling Layer: The network performs an additional max-pooling operation using a 2x2 kernel with a stride of 2, further reducing the spatial dimensions of the feature map.
- Flattening: The resulting feature map, now reduced to a size of 7x7 with 64 channels (following the two convolutional layers), is flattened into a one-dimensional vector. This step is crucial because the fully connected layers in the next stage of the network require a one-dimensional input to function properly.
- Fully-Connected-Layers: The flattened vector is then fed through one or more fully connected (dense) layers. In this diagram, it seems to go through a layer that expands the features to a size of 3136x128.
- Output-Layer: The final layer is also fully connected and has 10 units, each presumably corresponding to a class representing the digits 0-9. The network would output the probability of each class, and the highest probability indicates the model's prediction for each location of the character on the plate.

The final phase is the performance measurement. The proposed model is measured on both the training and validation datasets using standard evaluation metrics, including accuracy. This metric provides comprehensive insights into the model's effectiveness in character recognition tasks, capturing aspects such as correct classifications, FP, and FN. Here is the equation (2) of the Accuracy.

$$Accuracy\ (ACC) = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

To calculate accuracy, we add the number of correct predictions the model made (both TP and TN) and divide the sum of predictions made by the model.

4. Results and Discussions

In this part, a detail of the dataset will be presented. Additionally, this section will explain the outcomes of the model, focusing on accuracy. Visual representations of detection outputs will also be explained and comparative analysis will also be discussed.

4.1. Dataset Description

The proposed method for LPS and CR was rigorously evaluated using a diverse dataset consisting of license-plate-images (800) captured under a range of real-world conditions, as mentioned before. This dataset encompasses variations in lighting, perspective, and environmental factors to simulate the challenges encountered in practical scenarios. The upcoming Figure 3 illustrates the diversity of original Somali plate numbers included in our dataset. These plate numbers represent genuine instances encountered in everyday situations, ensuring that the model encounters a wide array of LP variations. This diversity allows the trained model to learn robust representations of Somali plate numbers and effectively generalize to unseen data.

4.2. Experimental Setup

The experiments are conducted within a Google Colab environment, which provides access to GPU acceleration to accelerate the training and evaluation processes of the model. Leveraging GPU acceleration significantly reduces the computation time required for training large-scale deep learning models, facilitating faster experimentation and iteration cycles. In terms of Programming Language, the proposed methodology is coded using Python benefiting from its libraries for machine-learning and computer vision tasks. Key libraries used in the implementation include TensorFlow for building and training the deep learning model, OpenCV for image processing and manipulation, and Matplotlib for visualization of results and performance metrics.

4.3. Result of License Plate Segmentation

The license plate segmentation algorithm successfully extracted license plate regions from input images. By applying contour detection and dimension-based filtering, the algorithm effectively localized license plates despite variations in size, orientation, and perspective. Figures 4 and 5 illustrate examples of segmented license plates.

Fig. 3 Somali plate

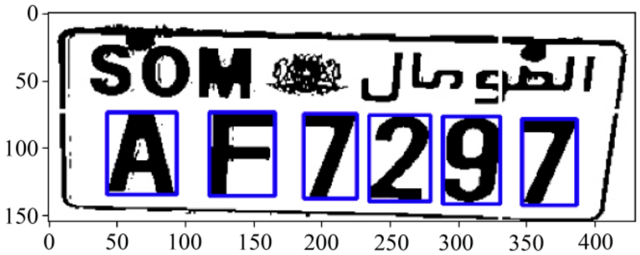

Fig. 4 Segmented license plate

Fig. 5 Output of segmented license plate

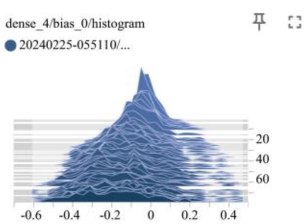

Fig. 6 Bias histogram

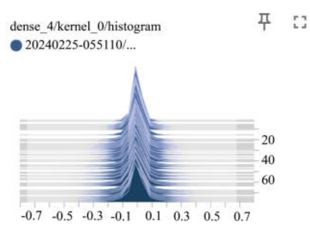

Fig. 7 Kernel histogram

After we had done Segmentation, we also monitored the behavior of CNN as you can see from Figures 6 and 7. As we can see from these two histograms that are the outputs from TensorBoard used to monitor and analyze the behavior of a CNN during training, we have monitored the Bias and the kernel of each, and we will discuss them. conv2d_2/bias_0/histogram: This histogram represents the distribution of the bias values for the second convolutional layer in your CNN model. Biases are parameters that are added to the OL before applying the activation function, and they work alongside weights to learn the appropriate features from the input data. The x is the value of biases, and the y shows the frequency at which these values occur during the training process across multiple epochs. From Figure 6, it can be seen that the bias is not even 0.2%. conv2d_2/kernel_0/histogram: This histogram shows the distribution of the kernel (or weight) values for the same second convolutional layer of your CNN. Kernels are the core of convolutional layers that perform the convolution operation in the CNN. They slide over the input image to detect features like edge textures.

The x-axis here indicates the kernel weights' values, while the y-axis shows how frequently these values appear during training. A kernel weight histogram that has a wide distribution and changes over time suggests that the network's weights are learning from the data.

4.4. Result of Character Recognition

The character recognition model displayed a remarkable level of accuracy when detecting characters on segmented license plates. The model was trained using a CNN and a set of labelled character data, allowing it to distinguish and classify different characters with a high degree of precision. After undergoing 80 epochs of training, the model reached an impressive 96.76% accuracy, underlining the effectiveness of the proposed approach. Such a high rate of accuracy indicates that the model was highly successful in assimilating the patterns and distinguishing features in the training dataset, which has enabled it to predict the characters on license plates with considerable accuracy. As a result of the model's accuracy, the predicted output for a sample license plate number is "AF7297". This output indicates that the model is capable of accurately recognizing and interpreting the characters within the LP image. The predicted PlateNumber "AF7297" reflects the successful classification of each character within the LP region, showcasing the robustness and reliability of the model's predictions.

4.5. Comparative Analysis

The development and implementation of ALPR systems across various countries have demonstrated the global demand for intelligent vehicular technologies. This comparative analysis considers ALPR systems from Somalia, Iran, Saudi Arabia, Brazil, and Lebanon, focusing on their accuracy, processing time, and contextual adaptability to local license plate characteristics, as can be seen in Table 1.

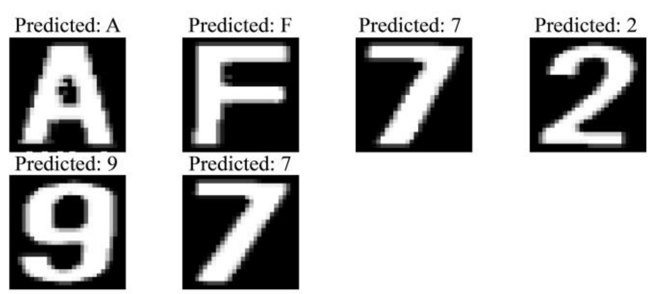

Fig. 8 Output of detected license plate

Table 1. Comparative accuracy and processing time

Reference	Sample Size	Country	Accuracy	Processing Time
Proposed Model	Training: 500 Testing: 200	Somalia	96.76%	101 milliseconds
[22]	Training: 1500	Iran	79.86%	1.9 s
[23]	Training: 13	Saudi Arabia	92%	1.20 s
[24]	Training: 800	Brazil	93%	5.5 milliseconds
[25]	Training: 420	Lebanon	90%	1.6 s

Our proposed CNN model, applied in Somalia, showcases the pinnacle of this comparative study with a striking accuracy of 96.76% and a remarkably swift processing time of just 101 milliseconds. This high-performance model, trained on 500 images and tested on 200, is a testament to the potential of deep learning in real-world applications, where speed and precision are paramount.

In contrast, the system developed for Iran [22], though trained on a significantly larger dataset of 1500 images, achieved an accuracy of 79.86%. While this system is tailored for embedded devices like the Raspberry PI3 and hence suitable for unsupervised parking lot applications, its longer processing time of 1.9 seconds may limit real-time application prospects. The model adapted for Saudi Arabia [23], trained on 13 images, successfully handled the complexity of Saudi LP, which features both Arabic and English characters and various symbols. Achieving 92% accuracy, the system leverages a bi-linear algorithm for image resizing and an ANN classifier for OCR. However, with a processing time of 1.20 seconds, it falls short of the proposed CNN model's processing efficiency. Moving to Brazil [24], the ALPR system attains a commendable 93% accuracy on a dataset of 800 images, excelling particularly in the segmentation and recognition of individual characters. This system's rapid processing capability is evident with a processing time of 5.5 milliseconds, suggesting an efficient use of convolutional neural network architectures despite the system's lower accuracy relative to the proposed CNN model. Finally, the system designed for Lebanon [25], trained on 420 images, takes advantage of the unique characteristics of Lebanese license plates to reach an accuracy of 90%. While its 1.6 seconds processing time does not match the speed of our proposed CNN model, it indicates a promising direction for country-specific adaptations. Overall, each system exhibits unique strengths tailored to its local context.

However, our proposed CNN model outperformed the other models in terms of accuracy and speed, setting a new benchmark for ALPR systems. This suggests that investing in more extensive training datasets and optimizing neural network architectures can result in significant performance gains, particularly when coupled with advanced computational resources.

5. Conclusion

This paper has come up with a novel approach for LPR in the context of IoT-enabled smart parking systems, leveraging deep learning techniques. Through extensive experimentation and evaluation, our proposed model has demonstrated remarkable accuracy and robustness in recognizing license plate characters, even under challenging environmental conditions. By training our model on a diverse dataset comprising Somali LP images, we have ensured its ability to generalize effectively to real-world scenarios.

The achieved accuracy rate of 96.76% after 80 epochs of training underscores the effectiveness of our approach in accurately classifying license plate characters. Furthermore, the successful prediction of the plate number serves as a testament to the reliability and practical applicability of our model in license plate recognition tasks. The proposed methodology implemented using CNN, TensorFlow, OpenCV, and other relevant libraries, has shown promising results and holds great potential for deployment in smart parking management systems across Somalia and beyond. Moving forward, future research efforts could focus on further refining the proposed model, optimizing its computational efficiency, and conducting field trials to validate its performance in real-world settings. Additionally, exploring additional datasets and incorporating advanced techniques could enhance the model's robustness and broaden its applicability to diverse environments.

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