**CHAPTER IV**

**PRESENTATION, ANALYSIS, AND INTERPRETATION OF DATA**

**4.1 The Developed System**

**4.1.1 Hardware**

**4.1.2 Software**

**Dashboard Graphical User Interface**

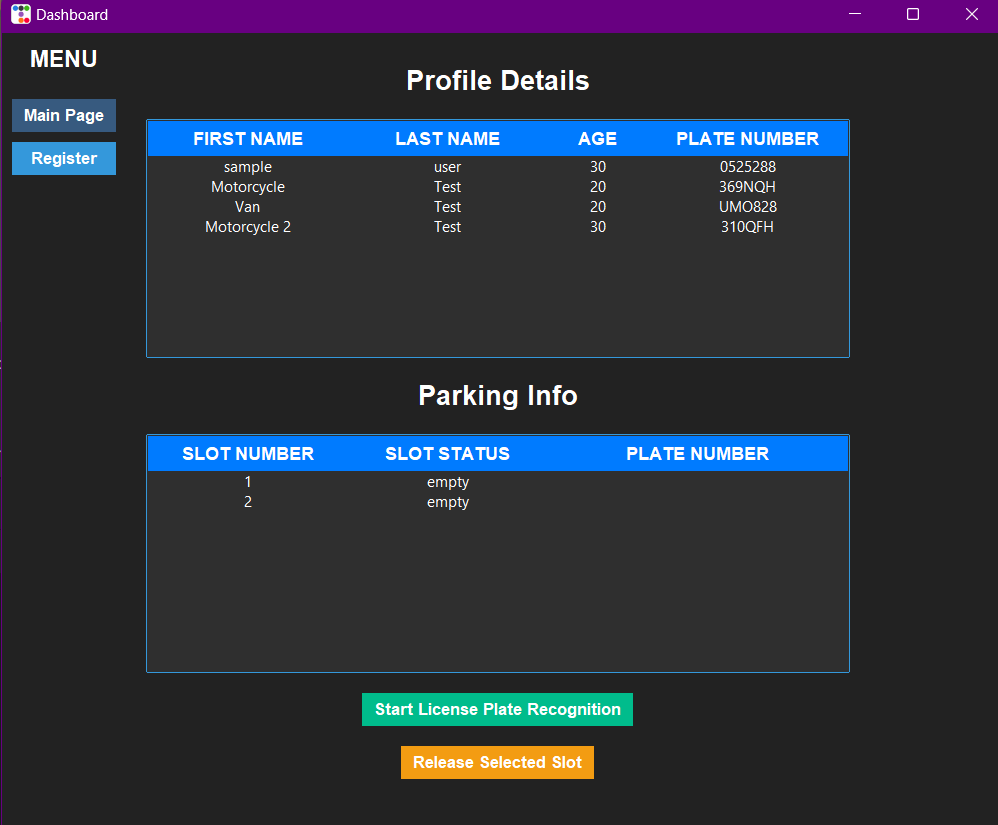
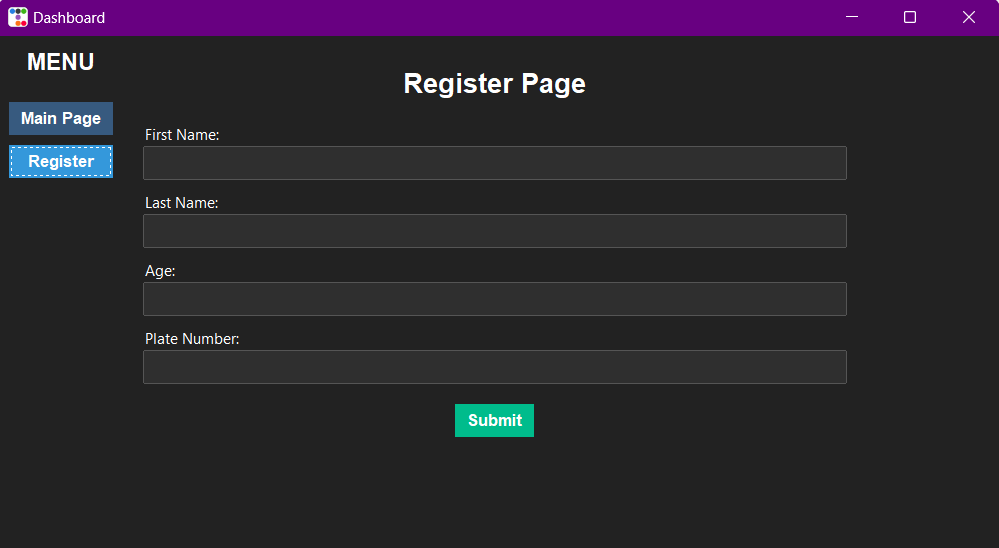


Figure #: Dashboard Main Page

Figure # displays the main page of the Parking System Software. The interface includes the profile details of the PWD (Person with Disability) user, featuring a tree view widget that lists their first name, last name, age, and license plate number. Below this section, the parking information status indicates the current availability of each parking slot. A slot labeled “empty” signifies it is unoccupied and available, while “occupied” denotes the slot is currently in use and unavailable. On the bottom side, two buttons serve different purposes. The green button initiates the license plate recognition if pressed, and the other button releases the parking slot when the vehicle needs to leave.



**4.2 Data Presentation**

4.2.1 Verification and Testing Result

4.2.2 Validation of Trained Model

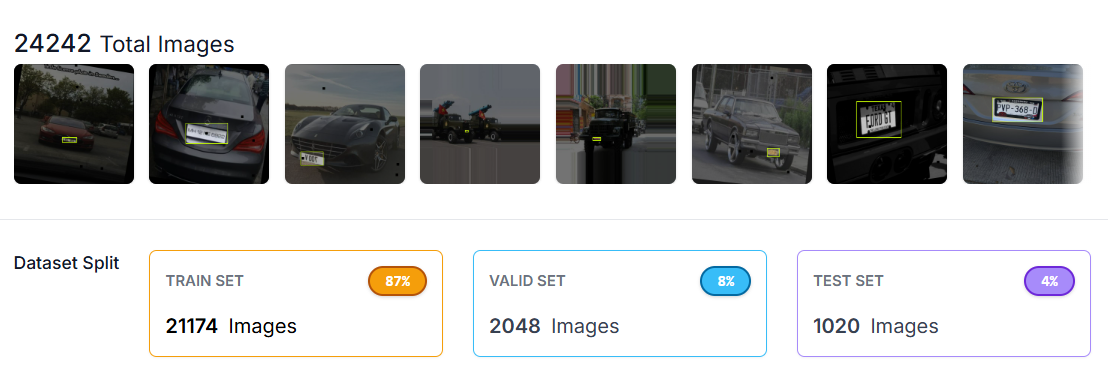
****

Figure # illustrates the total number of images utilized to train the license plate detection model using the YOLOv8 algorithm. The proponents employed software called “Roboflow,” which is a dataset management system that enables users to effortlessly upload, organize, and pre-process large datasets. The dataset was composed of 24,242 images of license plates and was divided into 3 sets. The train set comprises approximately 87% of the total images, the validation set consists of about 2,048 images, and the test set contains around 1,020 images.

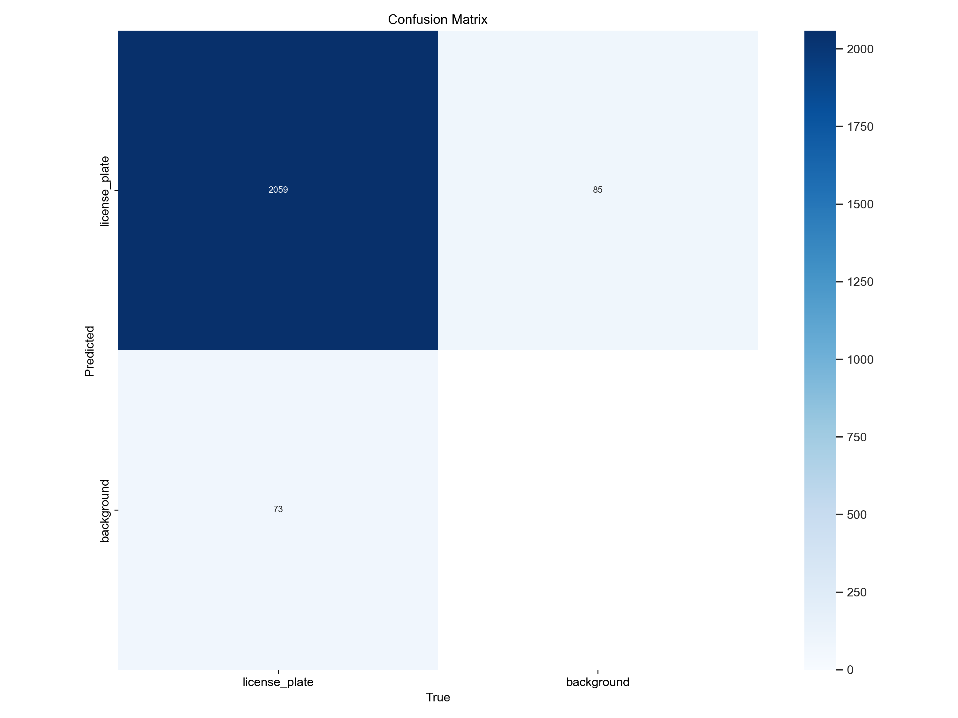
****

Figure #: Confusion Matrix

Figure # shows a custom‑trained YOLOv8 model demonstrating strong license‑plate detection performance. Out of 2,132 total plate‐containing images, it correctly identifies 2,059 plates, yielding a True Positive Rate (sensitivity) of 96.6 %. It fails to detect 73 real plates (False Negative Rate of 3.4 %), meaning it rarely overlooks actual plates. On the other hand, among all its “plate” predictions, only 85 (3.9 %) are incorrect false alarms on pure background regions (False Discovery Rate). The absence of true negatives indicates either that pure background cases were not included or that every background patch was at some point misclassified, suggesting future test sets should include explicit negative examples to better gauge specificity. The model reliably finds plates with minimal misses and low false positives.

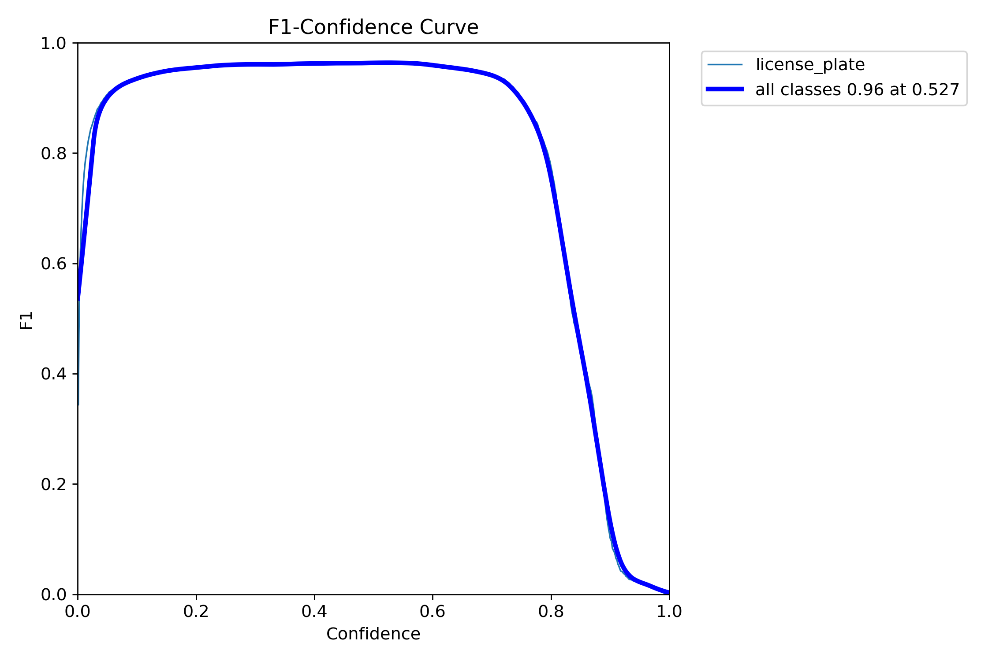
****

Figure # shows the F1-Confidence curve, illustrating how varying the detection threshold affects the model’s balance between finding real plates (recall) and avoiding false alarms (precision). At very low thresholds, the model labels nearly every region as a plate, so it catches almost all real plates but also produces many false positives, yielding a moderate F1 score. As the threshold increases into the mid‑range (roughly 0.2–0.8), the curve forms a broad plateau around an F1 of 0.95–0.97, indicating that the model maintains both high precision and high recall over this entire range. The maximum F1 of 0.96 occurs at a threshold of about 0.53—the same operating point used for the confusion matrix—where the model correctly detects 96.6 % of actual plates while only misclassifying 3.9 % of background regions. Beyond a high threshold (above ~0.8), the model becomes overly conservative, dramatically reducing recall and causing the F1 score to fall toward zero.

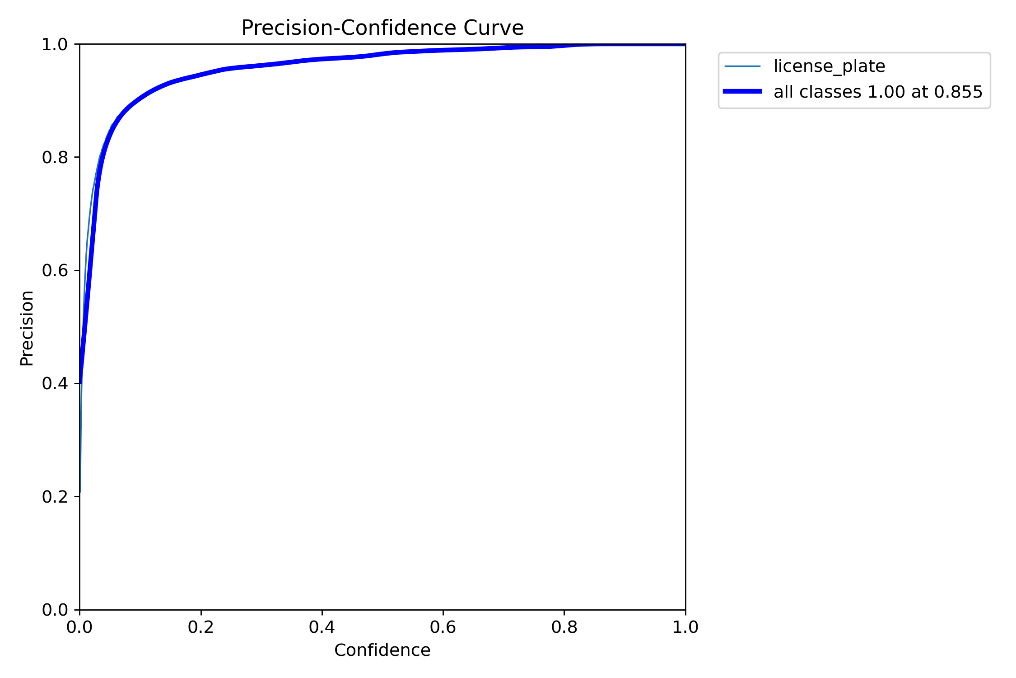
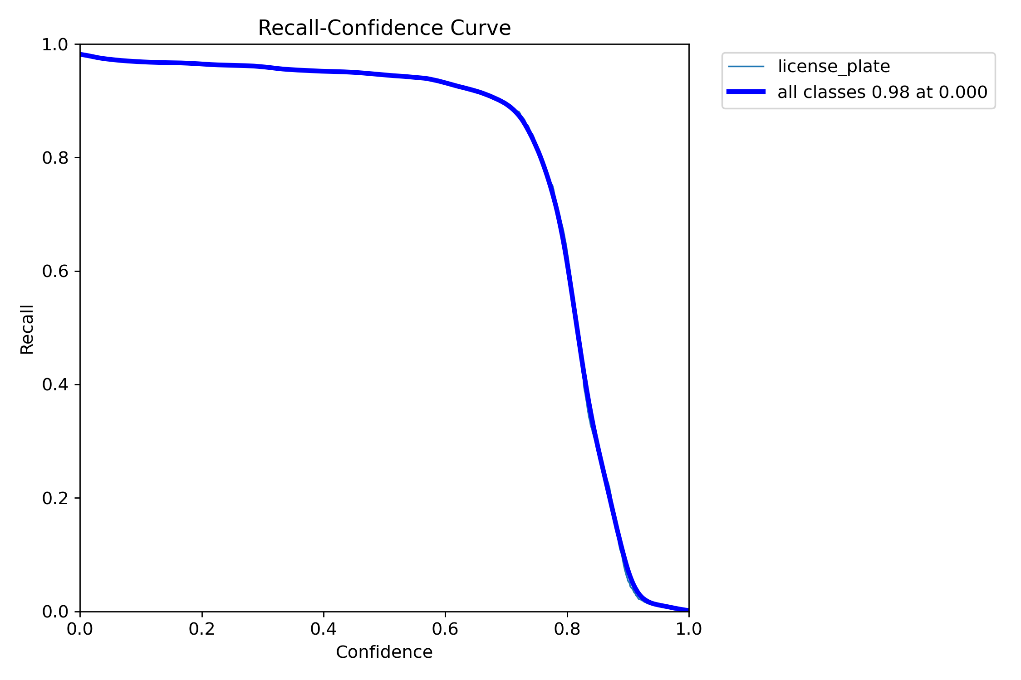
****

Figure #: Precision-Confidence Curve

Figure # shows the precision–confidence curve, which illustrates the relationship between the model’s detection threshold and its ability to suppress false positives. At very low thresholds (approaching 0.0), precision remains suboptimal (25–40%), as the model identifies nearly all candidate regions as license plates, resulting in frequent misclassifications. As the threshold increases, precision improves significantly: at a threshold of approximately 0.2, precision exceeds 90%, and it asymptotically approaches 100% as the threshold nears 0.855. At this critical threshold (0.855 confidence), the model achieves perfect precision (1.00), with no false positives observed. Beyond this threshold, the model adopts an increasingly conservative detection strategy. While all remaining predictions are accurate, this heightened selectivity comes at the cost of reduced recall, as the model fails to detect a growing proportion of valid license plates. This demonstrates a fundamental trade-off between precision and recall in the model’s performance.

****