The virtual environment designed for simulating traffic flow leverages the principles of CA. It features three distinct categories of vehicles (or agents): human-driven vehicles (HDVs), autonomous vehicles (AVs), and deviant human-driven vehicles (DHDVs). To effectively replicate the behaviors of these vehicle types we utilized the revised S-NFS model [19, 20] for HDVs, AVs, and DHDVs for their motion within lanes. The changing lane behavior is based on Kukida's model [21]. The DHDV agent incentive criterion differs from Kukida's model. If a vehicle in an adjacent lane is driving faster than a deviant vehicle, the deviant will change lanes to move in front of the faster vehicle.

III. Research Design

This research addresses the challenge of classifying a vehicle within a traffic flow by analyzing continuous observations of both the vehicle and its surrounding environment over a specified duration. Each vehicle is one the following types: AV, HDV or DHDV.

The classification problem is addressed utilizing classical supervised learning methodologies. The intelligent agent employed in this context is a recurrent Long Short-Term Memory (LSTM) neural network [13]. This agent is trained on a labeled dataset to accurately predict the type of vehicle it observes over a specified duration, measured in evolutionary steps.

A. Virtual Environment Parameters

Traffic flow is analyzed in the context of a two-lane road featuring periodic boundary conditions, effectively simulating a closed ring road. We conducted a comprehensive series of traffic flow simulations utilizing various parameters, as detailed in Table 1. The resulting dataset is compiled from these simulation outcomes.

TABLE I. Variation of Simulation Parameters

Simulation parameters	Variation range
Total number of vehicles	[100, 200, 300, 400, 600, 800]
HDV to DHDV ratio, %	from 70 / 0 to 0 / 70 in 10% steps

The other parameters were held constant across simulations:

- percentage of AVs is 30%;
- maximum vehicle speed $v_{\max}$ is 5;
- length of each lane set to 500 cells;
- number of time steps for achieving flow stabilization is 500;
- duration of evaluation phase is 1000 time steps (for dataset formation).

Consequently, the dataset was compiled from the outcomes of 48 traffic flow simulations, each consisting of 1,000 steps, encompassing all possible combinations of variable parameters (refer to Table 1).

B. Dataset Formation

The dataset consists of sequences of observations for each vehicle involved in the simulation. Each observation is represented by a matrix $\mathbf{M}_{obs}$, which encodes data about the tracked vehicle's speed, the relative positions and speeds of other vehicles within a certain vicinity of the tracked vehicle, and data about lane-changing maneuvers. The matrix is constructed based on the states of the CA within a specific region around the tracked vehicle (Fig. 1).

The matrix $\mathbf{M}_{obs}$ has dimensions $M \times N$, where $M = 2$ is the number of lanes and $N = W_{frw} + W_{bkw}+1$. The parameters W_{frw} and W_{bkw} define the size of the observation region in front of and behind the tracked vehicle, respectively. In this study, these parameters were set to equal values of 13.

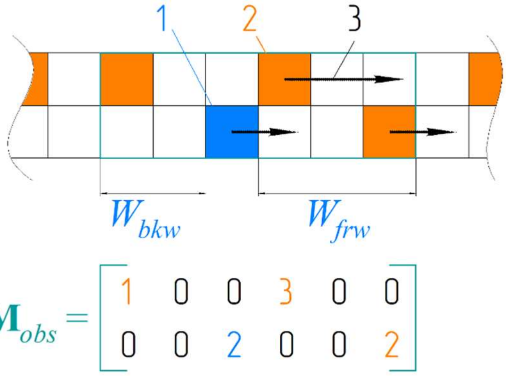

Fig. 1. Observation formation process: *1 – tracked vehicle; 2 – another vehicle in observation region; 3 – vehicle velocity*

Each element of the matrix $\mathbf{M}_{obs}$ corresponds to a CA cell located within the observation region around the tracked vehicle. Each matrix element M_{ij} is calculated using the following algorithm:

- If the corresponding CA cell is unoccupied by a vehicle, then $M_{ij} = 0$;
- If a vehicle occupies the corresponding cell, the value of M_{ij} is determined by the vehicle's current speed: $M_{ij} = v_{ij} + 1$ (so that stationary vehicles are distinguishable from empty cells);
- If the vehicle in the corresponding cell performed a lane change in the previous simulation step, the matrix element is multiplied by −1.

Each observation in the dataset is supplemented with a label y for the tracked vehicle, according to its type: 0 for AV, 1 for HDV, and 2 for DHDV. The final dataset contains 5760 consecutive observations (over 1000 steps each) for AVs, 6712 for HDVs, and 6708 for DHDVs, amounting to a total of over 19 million matrixes $\mathbf{M}_{obs}$.