# Detection and Recognition of Moving Biological Objects for Autonomous Vehicles Using Intelligent Edge Computing/LoRaWAN Mesh System

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**Abstract.** Currently, 5G/IMT-2020 networks with their possibilities become more and more services of new areas. These services are integrated into different human life activities. And in several cases, human life depends on Artificial Intelligence technologies, Autonomous Systems, and the Internet of Things (IoT), etc. Autonomous vehicles provide very strict requirements to the network in terms of ultra-low latency, high throughput, and wide coverage. To support these requirements, additional technologies must be employed. The current paper discusses the possibility of the use of airborne platforms aiming to support the terrestrial networks for autonomous vehicles realization as a part of delay-critical applications. Airborne platforms will help in the provisioning of safe road trips by delivering time-critical information to the vehicles globally, even in remote areas. In this paper, we discuss requirements and potential solutions for supporting the autonomous vehicle infrastructure, as a part of an intelligent transportation system. It's proposed to use a sensor network along the road, consists of energy-efficient sensors that can connect in a Mesh network. Also, a novel approach for the detection of biological objects activity on the roadside, based on Artificial Intelligence technologies are suggested.

**Keywords:** 5G/IMT-2020 · IMT-2030 · LoRaWAN mesh · Autonomous vehicles · AI · IoT · MEC


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## 1 Introduction

5G networks are designed to increase the speed of the wireless network so that it can transfer data that may reach 20 GB per second, and it's also can achieve a significant increase in the amount of data sent through non-wired systems that increase the circular range [1, 2]. 5G/IMT-2020 offers very important features, low latency (more responsive), big channels (speeds up data) and connecting more than one device at once (e.g. sensors, smart devices) [3, 4]. Software-Defined Network (SDN) is designed to make networks more flexible, it's also decoupling control and data plane. SDN provides much more efficient resources allocation and it's keeping in to in eye on the network services [5]. Also the network in SDN much more programmable, centrally managed and agile for any need, that means, we can use the SDN concepts in 5G to make the network more flexible [7, 8]. The main motivation to use SDN in 5G is that the system can be modified from a separating utilizing some consistent interfaces. Network Functions Virtualization is a virtualization technology for the physical network elements of a telecommunication network, when network functions are executed by software modules running on standard servers and virtual machines in them. These software modules can interact with each other to provide communication services that previously involved hardware platforms. The relationship between NFV and SDN is that the concepts of NFV originated from SDN, NFV and SDN are complementary, that means one does not depend upon the other, both have similar goals but, approaches are very different, SDN needs new interfaces, control modules and applications but NFV requires moving network applications from dedicated hardware to virtual containers on commercial off the shelf (COTS) hardware. The concept of MEC is to provide the placement of cloud IT resources for network virtualization closer to end users, on the edge of the carrier network. MEC uses the same principles as NFV and optimizes them for a radio access environment in mobile networks. MEC and NFV have in common the standard platform, open environment and Focus on programmability. Autonomous vehicles (AV) now use the 5G technology benefits to achieve low latency in data transmission [6]. In order to achieve low latency for AV, the network management entity must be proactive to make decisions about services that come from vehicles in time. Network Function Virtualization (NFV) release new possibilities within the network, and requires the addition of latest management and orchestration functions within the current model of operations, administration, maintenance and support. Older networks implement network functions (NFs), often associated with the infrastructure which they operate. NFV extracts software implementations of network functions from computing, storage, and network resources.

The rest of the paper is organized as follows: In the next section we overview the related works on 5G standardization with AV and MEC structures. In the problem statement clause we define the problem that we are going to solve in this work. In the proposed solution section we describe the architecture of our proposed solution for detection and recognition of biological objects activity, present the Mesh Network architecture, describe how it works and analyzing Mesh topologies and the functional diagram of the proposed solution. In Sect. 5 the main proposed Algorithm for recognition of biological objects was described. Section 6 shows the algorithm modeling to test the performance of the proposed method. In addition, Sect. 7 concludes the paper and discuss our future works.

## 2 Related Works

With the advancement of technology and the emergence of artificial intelligence, Autonomous vehicles have become the focus of attention of many industries. There has been a lot of research on autonomous vehicles in recent years. Projections indicate that autonomous vehicles will appear on the road further in the coming years [9]. Autonomous vehicles combine many technologies without the need for human intervention, help solve the traffic crisis, reduce accidents that may happen on the road caused by humans, reduce pollution caused by ordinary cars and reduce energy consumption [10]. MEC technology enables us to use cloud computing services and information technology environment on the edge of the core network and this would provide a quick response to autonomous vehicle services and improve the resource utilization. Road maps can also be stored and processed on MEC network servers. The MEC server can control computing services for a large number of autonomous vehicles, as the enhanced service area of the MEC server will support autonomous vehicles.

In [11] authors consider the achievements in the MEC networks development, as well as the main problems that arise when organizing a network architecture with MEC. Also three scenarios of interaction in networks with MEC were considered. In the first scenario, in addition to the three levels of network architecture represented by the end-user level, the level of the radio access network edge with the MEC servers associated with the base stations, the remote cloud server level, there is an additional level between the MEC servers and the remote computing cloud, which enables end-users to interact with MEC servers, remote cloud and with each other.

## 3 Problem Statement

Since the advent of cars, express roads between cities, there has been a problem of collisions with animals that suddenly cross the road. Because of that, terrible accidents occur, where people, animals and property suffer. Given the trend and the next step in the development of road transport, namely unmanned vehicles, it is worth considering the problem of accidents with animals from a new angle. In the case when someone is driving, he may notice unusual phenomena (shadow, bushes, etc., as well as warning oncoming drivers), which will allow him to reduce speed in advance and be prepared for an unexpected situation, including a collisions with animals. However, even considering human capabilities, animal accidents are not uncommon.

Therefore, as part of the development of the concept of autonomous vehicles and its infrastructure, it is necessary to consider the problem of accidents and develop an appropriate solution that will improve autonomous vehicles, as well as save the lives of people, animals and preserve property (vehicles, etc.).

Considering the technological advantages of 5G networks described above, in particular SDN /NFV network technologies, as well as cloud-based MEC and FoG Computing, there is a possibility of realizing our task, within the framework of the set requirements for the speed of the solution (delay from the trigger to autonomous transport), further forecasting the activity of biological objects. It is worth noting that this article considers the case of remote roads from residential areas (cities, villages, etc.), the length of the roads themselves, various weather conditions, the durability of the system, the possibility of its flexible configuration, scaling, and also the requirements for recognition type of biological object. In addition, in addition to the above-described capabilities that are laid down at the stage of developing the solution, it is necessary to provide for the possibility of further development of appropriate software modules for the tasks of predicting the movement of biological objects, taking into account digital models of infrastructure and autonomous transport.

## 4 Proposed Solution

### 4.1 Part One. The Common Architecture of Proposed Solution for Detection and Recognition of Biological Objects Activity

In the paragraphs of this article, which are described above, technological trends in 5G communication networks are defined, the capabilities of these technologies are described in a certain way, and a problem was described as a separate paragraph, the solution of which (the beginning of the solution) is the aim of this work. The posed problem of detecting biological objects in the roadside zone includes many complex system tasks, the solution of which, in turn, will allow to achieve a new level of road safety, especially in the framework of the concept of unmanned vehicles. This article discusses the concept of solving the problem, as well as the proposed method for organizing the infrastructure part and one of the analytical module that implements the methods of Artificial Intelligence.

Therefore, within the framework of the problem under discussion, a solution was proposed to use the technology of organization the cloud structures - MEC. This technology will ensure the feasibility of the criterion for the speed of the system, minimizing network and other delays introduced by an unnecessary part of the information and communication infrastructure. As a reader, it is proposed to use a network of low-cost sensors with LoRa MESH communication modules. The use of this radio technology will allow fulfilling the criterion for the remoteness of individual sections at roads from Base Stations, for energy conservation. As part of the task of processing the incoming data and the criterion of high reliability of analytical data, in this paper we propose the using the neural networks to recognize types biological objects.

Figure 1 shows the general architecture, including elements of the physical world (car, road, animals, etc.). Considering that this solution is proposed as part of an information system that includes two areas of analytical digital models: road and roadside infrastructure, autonomous transport. As already been found out in practice, an autonomous vehicle itself, with all the computing capabilities and machine vision technologies available today, will not be able to take into account a number of combinations of external phenomena and provide absolute safety for both passengers and everyone else. As a result, it is proposed to develop and considering data from digital models of roads and infrastructure, where autonomous transport is partly an independent structure. Interaction with each other should just provide the network and computing infrastructure of 5G communication networks.

Figure 1 shows the elements within the framework of this issue, as well as their possible interaction. One of the principles that was laid down in the requirements for the solution being developed is the feasibility within the remoteness of roads and, as

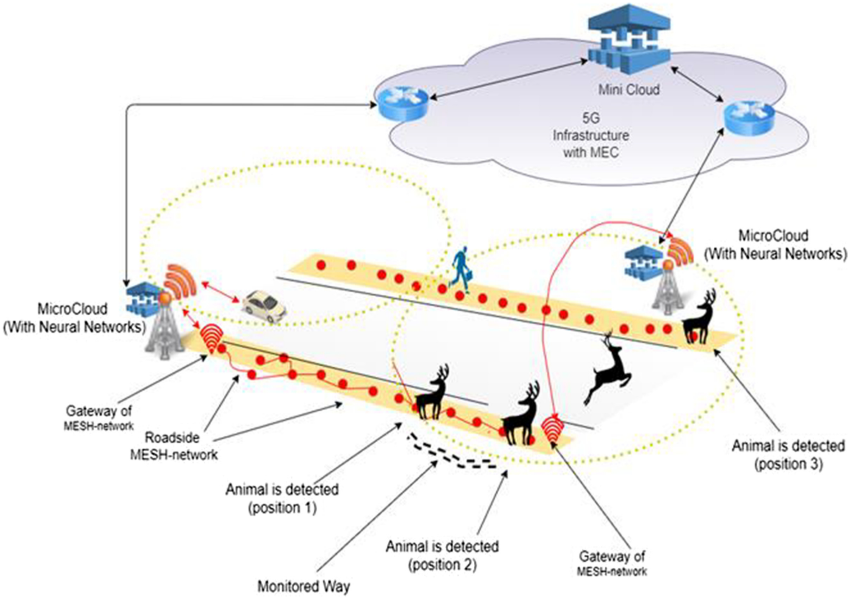


**Fig. 1.** The common architecture of solution

was already determined above, to fulfill this requirement, we proposed a new generation of LoRa technology. Thus, it is possible to transmit data from remote sensors that are located along the road along its curbs in several rows. After the sensor is triggered, its data is transmitted to the nearest MEC cloud, which is located at the nearest Base Station, so the entire roadside can be divided into "zones", which are also highlighted in circles with a dashed line in Fig. 1. When sensors are triggered and after data is transmitted to the nearest cloud, the primary data processing occurs, which allows to create the necessary data structure for the analytical module for object recognition implemented using Machine Learning technology. After that, certain messages are sent in a broadcasting manner to the nearest base stations, which broadcast the corresponding messages to the autonomous vehicles. In turn, these vehicles already knows in advance about the possibility of meeting a biological objects, determine their speed and time parameters and predict a further model of their movement. Thus reducing the likelihood of accidents that could have occurred if the autonomous vehicle relied only on the on-board sensor system and on-board video analytics system with machine vision. also noting that the proposed solution will just bypass the limitations of accident prevention, which are provided by the limited range of cameras and sensors. In the proposed solution, the car will know about the objects before the lidar or radar can notice, analyze and react, given the high speeds of modern and future automotive vehicles.

### 4.2 Part Two. The MESH Network Architecture and Protocols

Lora is Low Power Wide Area Network Standard (LPWAN), this term consist of three parts: 1) low power 2) wide area 3) network. The difference between a normal small device and an IoT device is its capability to connect to the internet, and because we expect millions of them, we need a network to connect all of them, this network has to be based on standards because the network itself and the IoT devices will not be built by the same company. Best is always an international standard accepted by everybody [12]. The next part is Wide Area, our devices can connect to our wi-fi network which is part of LAN or local area network, we all know that it's reach is limited to a few meters around our access points, wide area networks need to bridge much bigger distances. This is necessary for IoT devices because we are using them everywhere. The AM Radio Station is an example of wide areas, we were able to receive AM even in the middle of nowhere, far away from the station, but these transmitters were huge, usually they were emitting kilowatts of energy so it seems to be quite easy to bridge big distances using high power. The third part is Low Power, if we want to work on batteries, we don't have lots of power for transmission. And here we see the dilemma, we want kilometers of reach, but have no power to spend. Fortunately, physics gives as a third parameter to ease this dilemma a bit, it is called Bandwidth. The Physical laws say that if we want to create radio connection for a certain distance, we can either increase transmission power or decrease the bandwidth of the channel. We should bother about bandwidth because bandwidth and maximum capacity of a channel are directly related, the smaller the bandwidth, the lower the capacity of our channel. Today our wireless LANs are capable of transferring millions of characters per second, and they are still always too slow.

To understand how LORAWAN Mesh Network works, In the figure below sensor 1 is an intermediate link between sensor 4 and Network Server. When sensor 1 fails, sensor 5 takes the role as an intermediate and the connection between the server and sensor 4 is restored (Fig. 2).

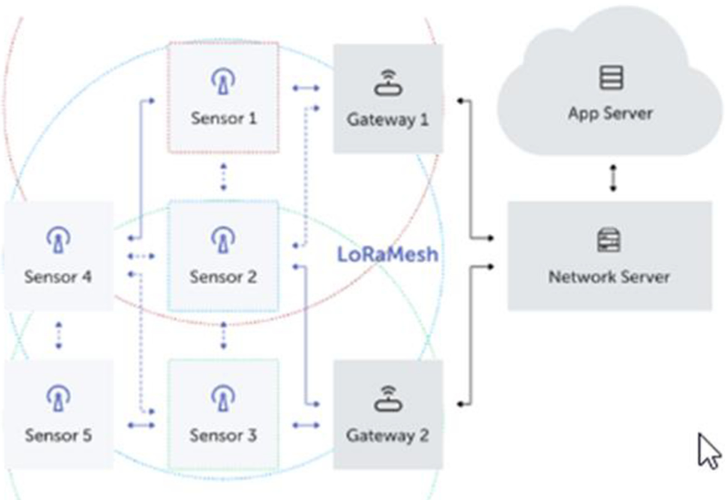


**Fig. 2.** LoRaWAN mesh topology

LoRaWAN Mesh network offers a reliable way to transfer data. The technology allows you to create large, flexible networks that consume little power. This makes the LoRaWAN grid one of the best ways to collect data from multiple remote sensors simultaneously.

### 4.3 Part Three. Computing Infrastructure

In Fig. 1, a generalized architecture of the proposed solution was given. Within the framework of the architecture under consideration, a number of elements have been identified that implement certain computing and network functions. The following Fig. 3 shows the functional diagram of the solution.

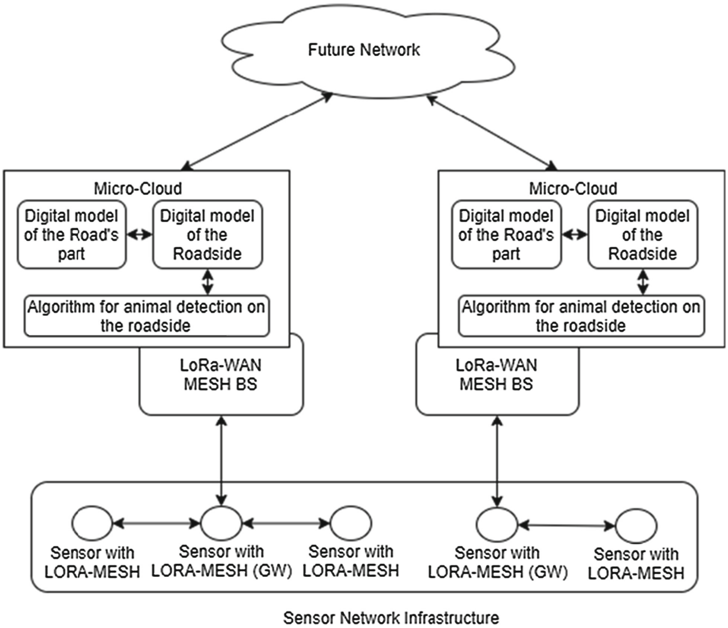


**Fig. 3.** The functional scheme of the suggested solution

Figure 3 shows the following elements:

1. Sensors with the LoRaWAN MESH module, for reading and subsequent data transfer via the Mesh network to the base station and to the virtual server;
2. LoRaWAN MESH base stations for aggregation of LoRa traffic and subsequent transportation of data to roadside clouds (Micro-cloud in MEC structure);
3. Within the framework of the Micro-Cloud, the corresponding server analytic application is deployed, which consists of the following main modules:

   – Algorithm for animal detection on the roadside. This algorithm is implemented on the basis of the architecture of recurrent neural networks, pre-trained to detect the corresponding biological objects;

– Digital model of the roadside. This module is a software package that implements roadside mathematical models, stores data, processes them for further transmission, as well as higher-order analytical models - for example, a forecasting system;
– Digital model of the road's part. This module is a software package that implements mathematical models of a part of the road infrastructure controlled by the cloud. This software provides, stores, processes data on the entire traffic situation and management of dynamic road elements (for example, a railway crossing, etc.). Based on these data, certain predictive analytical data are generated for the development of the corresponding section of the road, any incoming autonomous vehicles are informed, by transmitting the requested data by the vehicle's on-board system.

## 5 Proposed Algorithm for Biological Objects Recognition

Here, we propose a new algorithm that help recognising the biological objects when one if those cases is beside the road and trying to cross it. Cases that we are going to recognize:

1. One person
2. A group of people
3. Deer

The figure below shows sensors map in two adjacent zones (Fig. 4).

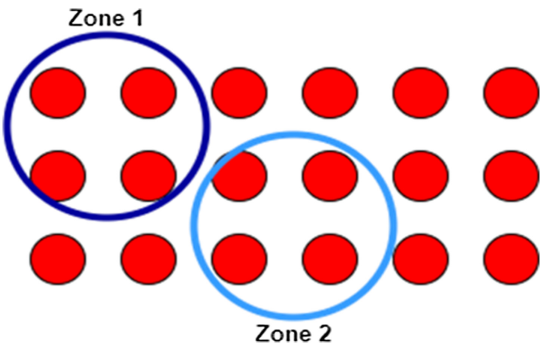


**Fig. 4.** Map of the sensor's zones

### 5.1 Data Processing

The number of active pushed sensors in one zone (4 m).

$$N, N \in M$$

$$M := [x, y] = [3, 4] = 12;$$

T (Response Time) Delta between sensors from adjacent areas:

$$Ts = Ts\_(1\_1) - Ts\_(1\_2);$$

*Ts* 11 - response time of the first sensor in the first zone, *Ts* 12 - response time of the first sensor in the second zone.

Sum of Forces (F) of pressed sensors in one zone: $F = \sum\_(n=0)\hat{}N\ F\_(n),\ N \in M$

Average sensor press time in one zone: $\Delta T\_avrg = (\sum\_(n=0)\hat{}N\ \Delta t\_n)/N,\ N \in M$

The distance between the first pressed sensor in the first zone and the last pressed sensor in the second zone:

$$S = \sqrt{}\left((N\_12 - N\_11)\hat{}2 + (N\_(22) - N\_21)\hat{}2\right)$$

## 5.2 Neural Network

Today, an artificial neural network is widely used to solve various problems in various aspects in our life. For example, the areas of speech recognition, computer vision (a complex integrated video analytics of graphic objects), recently - complex engineering systems and their modules (for example, oil refineries automobile plants and so on). Such complex tasks of analyzing large volumes of information are solved by developing tools belonging to the Artificial Intelligence class. One of the most developing methods for predicting models based on large amounts of data is artificial neural networks, a variety of which is already large at this stage of development of these technologies [13].

At the moment, there is a large variety of neural networks. One of the typical tasks is classification. One of the most common classification methods is a method based on descriptions objects using signs, in which each object is characterized by a set of numerical or non-numerical signs. However, for some types of data, open features do not give a classification accuracy, for example, the color of image points or a digital audio signal. The reason is that this data contains hidden features. Deep Learning is a set of machine learning algorithms that try to model high-level abstractions in data, in other words, extract hidden features from data [14]. Therefore, considering the features of the object (traffic) and its attributes (numerical - statistical series), a neural network with Deep Learning was chosen.

To solve the recognition of a biological object, considering the peculiarity of the incoming data for our task, as well as the requirements for the system under study and development, a recurrent neural network was chosen as NN.

Since the chosen architecture for the neural network implements the principle of training with the involvement of a teacher, it is required to compose training Datasets with marked data, then save the state of the trained network. To train the neural network, the input $DataSet_{ML}$ was converted to $DataSetML_{train}$ by adding a new data column, each row had the identifier of the statistical sample. Accordingly, for training to recognize a larger type of traffic, this training Dataset needs to be expanded by marking the corresponding statistical sample with a label of a biological object, e.g. Deer, Human or Human Groups. Thus, the structure of the training $DataSetML_{train}$ is as follows:

| [Type of BO] | [ActiveSensZone] | [TimeFirstSen] | [ForceSumm] | [deltaTime] | [distance] |
|---|---|---|---|---|---|
| Deer | $N_{11}$ | $Ts_{12}$ | $F_{13}$ | $\Delta T_{avrg_{24}}$ | $T_{15}$ |
| Humm | $N_{21}$ | $Ts_{22}$ | $F_{23}$ | $\Delta T_{avrg_{24}}$ | $T_{25}$ |
| Group.Humm | $N_{31}$ | $Ts_{32}$ | $F_{33}$ | $\Delta T_{avrg_{34}}$ | $T_{35}$ |
| … | … | … | … | … | … |
| … | $N_{N1}$ | $Ts_{N2}$ | $F_{N3}$ | $\Delta T_{avrg_{N4}}$ | $T_{N5}$ |
| others | $N_{(N+1)1}$ | $Ts_{(N+1)2}$ | $F_{(N+1)3}$ | $\Delta T_{avrg_{(N+1)4}}$ | $T_{(N+1)5}$ |

The network model contains 4 fully connected RNN layers, each of which contains 12 hidden nodes.

The hyperparameters of learning:

- Optimizer: Adam;
- Number of epochs: 60;
- Number of samples per iteration: 1024;

Learning speed: 0.0025

# 6 Results

To test the operability of the proposed method for detecting a biological object on the roadside, a data generator was developed according to the formulas and tolerances defined above. As a simulation, a simulation model was developed in Python programming language, with an artificially recurrent neural network implemented. After the Dataset was created, the developed neural network was activated, after its successful training, the state of the neural network was preserved (the resulting architecture, weights, and other parameters). This neural network has the ability to further refine and implement on the stand, in order to pilot the solution.

Using the model data generator with subsequent processing, a DataSetML_train was formed, and fed to the input of a neural network, the configuration of which is shown in the article above.

During training, the parameter 'accuracy' was monitored - the function inverse to the error function in recognition of activity and the parameter 'loss' - cross entropy determining a slightly near-predictable distribution to the true one.

It is expressed as follows (Fig. 5):

Also, in addition to the graphs shown in Fig. 5, the Confusion Matrix of neural network training was calculated and built. The matrix is displayed in Fig. 6.

In the figure, where the Confusion matrix is displayed, it is clearly seen that for the task, the network has successfully completed the training process. As a result of training the developed neural network and testing its operation on test Datasets, in a trained state, the developed neural network can identify the type of biological object with a probability of 99.8%. Using the Confusion matrix, you can see that the network made a mistake 3 times. It is also worth noting that the selected architecture was an effective


**Fig. 5.** Machine learning process

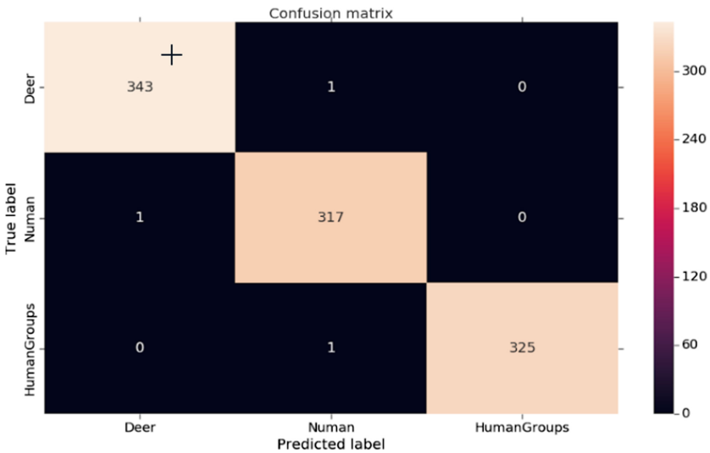


**Fig. 6.** Confusion matrix

solution to the task. With a lower value of neurons in the embedded layers, the artificial neural network does not work stably, and it also does not reach the appropriate level as an object detection and makes a significant number of errors. With a larger value of the number of nested neurons, the network also does not work stably and the effect of "retraining" the network occurs, it was possible to judge those graphs that were obtained as part of the study of the NN architecture and its training on test data. It is also worth noting that the schedule of the learning process contains a sharp jump in the quality of training an artificial neural network at the time of the 40th era. The graph should have a smoother character. However, in this task, various characteristics of the neural network were investigated and those that are given in this article are more efficient and fulfill the task of testing the proposed solution.

## 7 Conclusion and Future Work

In this paper, we present a solution to detect and recognize the biological objects activity on the roadside. This solution can help alleviate accidents caused by animals or people on the road. We have used MEC technology that has system speed specifications and reduces network delays when transmitting data through it. LoRa mesh wireless technology was used to provide data transmission between highway remote networks and the main station. We proposed an algorithm to identify the movement of people and animals on the highway, in this algorithm we used the neural network, a network that is widely used in various fields. This network solves many complex tasks that contain large amounts of data. Artificial neural networks are one of the most sophisticated methods for predicting models based on large amounts of data. We also proposed an algorithmic model to test the operability of the algorithm that we proposed by developing a simulation model in the Python programming language, with the implementation of an artificial neural network. This work aims to develop a new mechanism to detect the movement of people and animals on the highway and their roadsides, expand the digital roads models for provides the new AV possibilities. In the upcoming works, we will aim to use the proposed algorithm by analyzing the data in more detail, which would help to further mitigate the accidents that could happen on the road.

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