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Delivery Time Prediction for On-Demand Delivery Services using Deep Learning

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Abstract

In big cities, like the capitals of a country, logistics companies are worrying about making Just-In-Time deliveries. However, there is uncertainty in estimating travel time for in-city delivery.In this research, we propose a deep learning model to predict delivery time based on registered order data, we design a hybrid approach that contains components such as: deep feature learning, feature adaptation and classification. The model has been trained with 800 patterns and 200 tests which were taken by a logistics company. The results of the computational experiments show that the proposed model reached an accuracy percentage of 82.7%.

Keywords:*time prediction, deep learning, artificial neural networks, GAN, CNN*

I. INTRODUCTION

Increasingly, artificial intelligence algorithms are used to solve different problems such as heart disease detection [13], tuberculosis detection [17], information search and retrieval [14], augmented reality [15], recommendation of videogames [18] and many other purposes. On the other hand, logistics companies are worrying about making Just-In-Time deliveries. However, the uncertainty involved in estimating future travel time and the lack of reference points, designed with the travel time as the main cost, hinder the development towards an optimal logistics planning system [1].
In the area of on-demand delivery services in Peru, there is Urbaner. It takes care of the logistics of the shipments and helps local businesses to focus on their line of business [2].

When a user generates an order, they are not given the approximate time which their request will be attended or the estimated time in which the delivery personnel will arrive at the requested point. The estimated time is a priority for the user to have the package prepared. In this way, waiting times would be greatly reduced, deliveries would be more efficient, and it would mean greater profitability for the company.

In the classic vehicle routing problem, the algorithms are developed according to the distance or estimated travel time from an assumed constant travel speed. However, in logistical aspects of the city due to an increasing amount of traffic and a limited capacity of the road network, the travel speed is no longer a constant, but rather dependent on location and time[3]. That is why it is necessary to consider the data of latitude, longitude, destination series, day, hour and minute.

In a multilayer neural network, it is not possible to abstract to an acceptable level the behavior of the

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geographical areas in relation to the hourly aspect of a highly urbanized area, on the other hand, in [4] they present a convolutional neural network architecture for financial prediction.

In this research we propose a delivery time prediction model for on-demand delivery services using deep learning convolutional networks and generative adversarial networks (GAN).

The rest of the document is structured as follows: Section II provides the State of the Art, reviewing the relevant literature. Section III we present the proposal. In Section IVthe results obtained and discussions.

II. STATE OF THE ART

Analyzing previous works, [1] presents an alternative for estimating travel time between two locations connected by a network of urban roads. The authors propose the use of GPS sata from the logistics fleet to incorporate the experience of drivers for abettwe approximation of travel time and driving paths, they analyze the absolute errors of the estimation results, show that the proposed algorithm is in accordance with the Bing map service for the purposesof reference design and route planning. In logistics, the authors apply Dijkstra's algorithm with implementation of preferences for highways and shorter travel time. The results of the algorithm were largely in agreement with those of the Bing map service, as more than 90% of the absolute error values were between 0 and 10 minutes.

Taking into account that the travel speed between two points is no longer a constant, but dependent on the location and time, the researchers in [3] propose a framework to visualize the traffic condition at different times and different locations in Singapore, through the estimation of the travel speed between either of the two locations based on Google traffic data. They first divided Singapore into zones according to the Postal Code System. They then estimated travel speeds within and between zones by randomly sampling pairs of locations and calculating travel speeds between them.They also studied in detail the sample size, the accuracy of the estimate, the relationship between the mean and the standard deviation of travel speed and travel distance.In terms of relative deviation in speed, 87.18% of the sampled arcs are within 5 minutes of the deviation of the estimated travel time.

In [5] they investigated the effectiveness of implementing unmanned aerial delivery vehicles in delivery networks. They also studied the notion of reducing overall delivery time and energy for a network of truck drones by comparing the in-tandem system with an independent delivery effort. They then conducted various experiments using the optimization algorithm and formulated approximation mathematical models as mathematical solutions for the expected delivery time and the optimal number of stops. At the end of this study, the results showed improvements with in-tandem delivery efforts compared to independent systems. The algorithm was shown to be able to solve problems with 200 or more clients in approximately two minutes. The algorithms found the optimal number and location of truck stops.

In [6] they seek to obtain reliable arrival times. The authors conducted a literature review to find the factors that provide information to predict arrival time: congestion, weather and time of day and incidents.To validate the factors that influence arrival time, the authors conducted a detailed case study that included a survey of 230 truck drivers, a data analysis, and a data mining experiment, using real traffic and weather data. These showed that, while a big data approach provides valuable information, the predictive power is not as high as expected; other factors such as human or organizational factors, could influence arrival time and they concluded that such organizational factors should be considered in future predictive models.

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The objective of the authors in [7] is the prediction of the delivery time that affects the logistics route, depending on the needs of the place and the quantity, they explained that an efficient prediction of the delivery demand would help the construction of a logistics model, the data on delivery demand depends on time and spatial correlation. This study proposes a new prediction for the logistics delivery procedure from the space-time perspective, the researchers created a long-short-term-memory (LSTM) network with two-dimensional input to discover the spatio-temporal correlations between the ocurrences of delivery request and exploit correlations to make accurate demand predictions. By simulating the proposed LSTM network, they found that the prediction accuracy of the test data was 74.81%. From this, they concluded that the performance of the predictions was significantly better than the one-dimensional inputs and that the correlation of spatiotemporal data does provide a better prediction than the extraction of time series data.

Estimating the delay time of buried target echoes is particularly important for ground penetrating radar (GPR) application.Due to its lower computational load, the estimation of signal parameters using the rotational invariance technique (ESPRIT) is preferable to process the target echoes buried in the frequency domain and to obtain the time delays with high precision. Article [8] provided an in-depth analysis of essential pre-processing steps for applying ESPRIT to practical GPR measurement data.In particular, the authors adopted an improvement of the spatial smoothing method to construct the matrix correlation for the robustness of the delay time estimation result.They then verified the effectiveness of the algorithm using the synthetic data of a horizontally stratified median model using the finite time domain difference method, which explicitlytakes into account the surface spread for a more realistic scenario. The estimation results of the FDTD simulation data demonstrated that ESPRIT, with the ISS, scheme, can improve the resolution of closely spaced buried echoes. They also demonstrated that the ISS method can outperform the traditional MSSP method by estimating the extremely overlapping buried target time delays.

The research carried out in [9] presents a method to predict the delivery time of packages in spatial internetworks. The Bundle Delivery Time Estimation (BDTE) tool exploits Contact Graph Routing (CGR), predicts the packet route, and calculates plausible arrival times along with corresponding probabilities. The authors analyzed that their method can be used for administrative purposes and can provide delivery time expectations for critical bundles. Plausible delivery times can also be computed early, and delivery probabilities can be anticipated before a given time.Therefore, BDTE could provide a useful administrative tool to predict the performance of different spatial applications and adjust their functionality and use in real time.

In another investigation [10], the authors identified assisted home delivery (AHD) as a crucial delivery mode in the last mile problem.AHD involves the delivery of the necessary goods at or near the customer's doorstep, on foot or in short-distance vehicles.Taking into account the random response time, in this research they present an integrative approach that combines appointment scheduling and the vehicle routing problem with smooth time windows. Furthermore, the researchers propose an intuitive heuristic dynamic programming to address the appointment scheduling problem, the optimal decision of which is expected to be very complicated to embed it in a taboo search and formulate a hybrid heuristic algorithm to solve this integrative model. The results indicated that the integrative approach could lead to high-quality solutions in a reasonable number of executions compared to the hierarchical approach.
Article [11] considers the problem of estimating delivery times for orders arriving dynamically in a

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flexible flow shop. When an order arrives, the time between its arrival and its completion is estimated. A good estimate would help improve delivery time. Existing information methods are mostly designed based on the processing time of an order and the status of the store's inventory. This study tries to improve the accuracy of the estimation by developing new methods that also take into account the characteristics of the existing system, such as queue parallelization. The authors propose two methods for estimating delivery times in a flexible flow shop. Finally, they designed the proposed methods based on the idea of parallelizing queues and waiting times, as well as considering the action of the bottleneck effect, and carried out simulations to evaluate the proposed methods using a large number of randomly generated problem instances. The results showed that the proposed methods outperformed existing methods in terms of both accuracy and stability.

Container flow information is a critical problem for port operators to support their strategic planning and decision making [12]. This study uses artificial neural networks to predict container flows considering GDP, interest rates, the value of export and import trade, the number of export and import containers and the number of quay cranes.

What is mentioned in [11] concludes with an improvement in accuracy and stability,however, the proposed methods only contemplated the number of orders that arrived at the store and the orders that were in queue for delivery. Although the aforementioned attributes could be optimized, they do not contemplate the delivery time of the order to the customer, which is an important factor that is considered in [1], where the Dijkstra algorithm was applied and the choice of the best roads to travel and the choice of those that took less time for delivery was taken. The aforementioned algorithm could be taken to reinforce the methods used in order receipt and thus obtain a more efficient receipt-delivery flow than what had already been found.

Likewise, both in [1] and [3], an approach is proposed on improving the delivery time of the order to the customer, but in different ways: one on the optimization of the delivery route and the other focusing in the travel speed to make the delivery, for which the knowledge generated in the investigations could be combined to obtain an even more efficient and accurate way, with a space-time attribute that defines a shorter delivery route at a faster delivery speed.

In the same way, the research presented in [6] can take advantage of the knowledge obtained in [1] and [3]. This is also based on optimizing delivery time by adding the "human factor", an attribute that is not considered in [1] and [3], taking into account the knowledge that an expert, in this case the truck driver or the person in charge of delivering the order, you can provide in terms of the departure time to make the delivery and the routes that are part of your knowledge. We can replace the known paths with those that are generated by the algorithm of [1], often being new to the person in charge of delivering them; in a second route, these would already form part of the knowledge of the person in charge and the application of the "human factor" and the speed of delivery investigated in [2] could be carried out.

III. DESIGN OF THE DELIVERY TIMES PREDICTION MODEL

Attributes for the proposed model

We consider that to predict the delivery times, the attributes that allow training our model are very important, such as: the delivery point, the order in. Which the products are being delivered, the delivery or pickup of a product and the exact time in a determined day, so we consider the attribute that we present in Table I.

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TABLE I. IMPORTANT ATTRIBUTES FOR TRAINING

Attribute	**Description**
Latitude	Latitude where the delivery point is located on the map.
Longitude	Longitude where the delivery point is located on the map.
Number	Defines the delivery number of the same product, that is, if a product has a number 2, this product is the second to be delivered from a line of “n” products. For each delivery there is a different number that can belong to the same product.
Task	If the value is “1” then it refers to a delivery of an order, if the value is “0” it means that it points to a pickup of an order.
Day	Day of the month that was requested (only the number of the day).
Hour	Hour the order was placed. It is based on a 24-hour format. Hour and Minute make up a single order hour.
Minute	Minute the order was placed. Hour and Minute make up a single order hour.

Proposed arquitecture

We designed a deep learning architecture that calculates the time required for each delivery accurately based on the data of the registered orders. In Figure 1 we illustrate the various steps involved and then we propose a hybrid approach that contains the components: deep feature learning, adaptation of characteristics and economic classification of the sectors of Lima Metropolitana in this case.

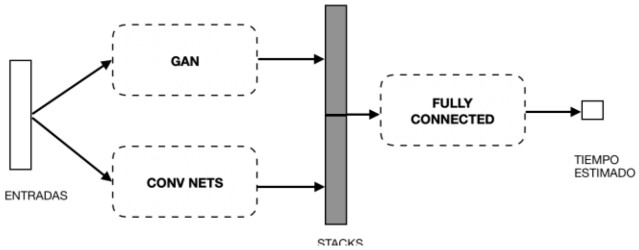

Fig. 1. General architecture of the prediction model.

We represent the inputs according to Table I, we add a GAN architecture and the CONV NETS architecture (CNN) for learning temporal and spatial characteristics in parallel. Next, the learned temporal characteristics X and the spatial characteristics Y are combined in the stacked characteristic STACKS for the adaptation of the last characteristic and finally obtain the estimated time. Next, the proposed architecture is explained in detail:

- Learning and generation of GAN characteristics: It is a kind of deep neural network, which explores the dependencies of the characteristics over time. The GAN structure has a powerful capacity for the extraction of temporal characteristics in time series data, in this case we consider for delivery and pickup orders, so we design a GAN model that we present in Figure 2, which consists of three components: an input layer, 5 hidden de-convolutional layers, and an output layer. Furthermore, experiential experiments show that the trigger function cannot improve GAN performance, but rather bringsoverfitting.

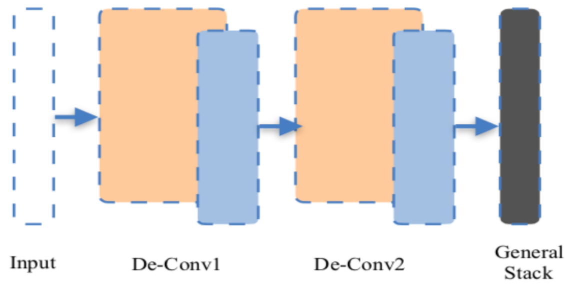

Fig. 2. Learning and generation of GAN characteristics.

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- CONV NETS architecture (CNN): While GAN is good at exploring temporal relevance (between samples), the CONV NETS structure is made up of three layers: Con1 is the convolutional layer, Con2 as the grouping layer, and Conv3 as fully connected layer. The convolutional layer contains a set of filters to convolve with the data and then through feature grouping and nonlinear transformation to extract the geographic features. The step denotes the x y movements, the distance and the y movements of the filter, the ReLU activation function designed to work on the convolutional results was used.

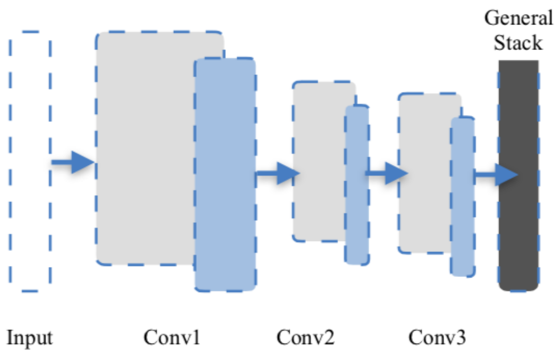

Fig. 3. CONV NETS architecture(CNN)

- Feature adaptation and prediction: Subsequently, as shown in Figure 4, a feature adaptation method was designed to map the stacked features to a new correlative feature space that can merge temporal and spatial features and highlight useful information.We introduce the Autoencoder layer which is an unsupervised approach to learning effective features. The cost function measures the difference between the estimated ETA time and the actual time used as MSE (mean squared error), that is propagated back to the algorithm to adjust weights and biases. The error is optimized by the RMSPropOptimizer. The data in the hidden layer is the transferred entity, which is sent to the classifier. Finally, the extreme gradient boosting classifier (XGBoost) is used to classify geographic data streams.

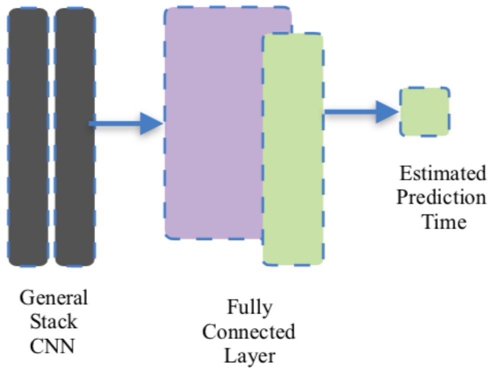

Fig. 4. Adaptation and prediction of characteristics.

Model output

Table II describes the attributes that make up the outputs for each test data.

TABLE II. ATTRIBUTES OF THE OUTPUT

Attribute	Description
Hour	Approximate time the order will be delivered. It is based on a 24-hour format. Hour and Minute make up a single delivery time
Minute	Approximate minute in which the order will be delivered. Hour and Minute make up a single delivery time.
Hour delay	Approximate number of hours that it will take for the order to arrive at its destination. This works together with the "*Minutedelay*".
Minute delay	Approximate number of minutes it will take for the order to arrive at its destination. This works together with the "*Hourdelay*".

Design of the application with the proposed model

The proposed model will be integrated into a service bus, which is in charge of real-time tracking of each element of the system.

```
+-------------+      +---------+    WebSocket    +-----------+
|   Storage   |      |  API *  | +-----------►  |  Browser  |
+-------------+      +---------+        (3)      +-----------+
       +               (2) ▲
       |                   |
   (1) ▼                   +
+-----------------------------------+
|                Bus                |
+-----------------------------------+
```

Fig. 5. Adaptation of the existing ecosystem.

In Figure 5 the adaptation is described, the browser established a WebSocket connection with the time estimation API, which is consumed for the Bus server. Upon receiving a new request, Storage send a notification about it to the Bus and the bus to the API. The APO determines the connection to send the information to the client. Storage is designed in redis-gis, which keeps requests cached. The API and the WebSocket are implemented in Go.

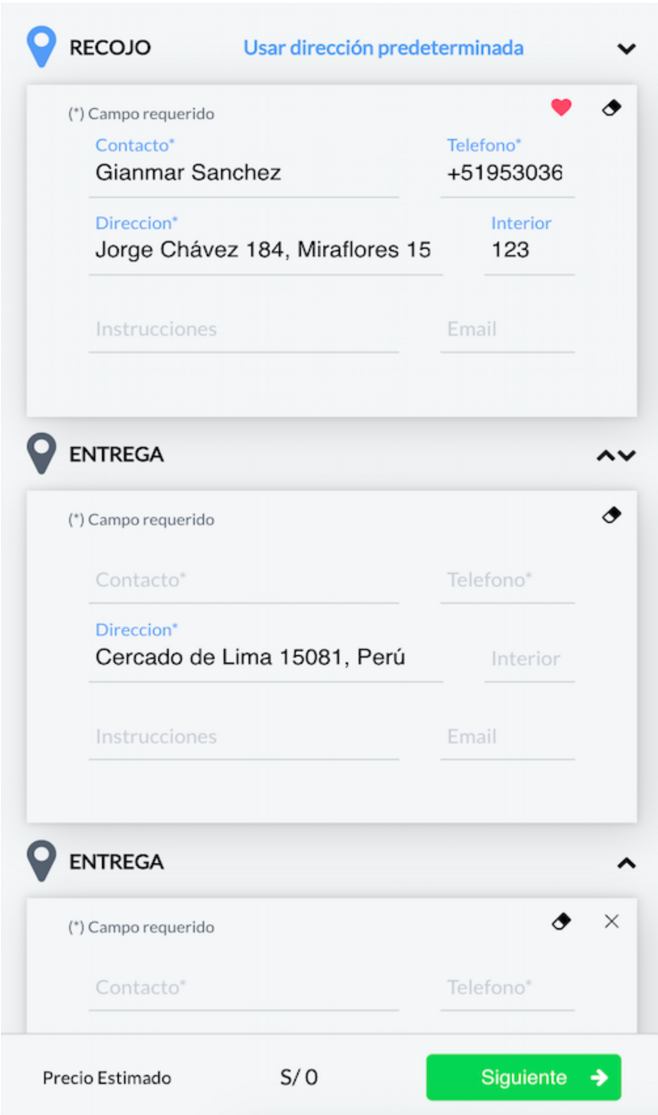

Fig. 6. Graphical interface of the web system to add addresses.

The graphical interface of the existing system is displayed. Figures 6 and 7 show the graphical interface of the web system, while Figure 8 shows the graphical interface of the mobile application.

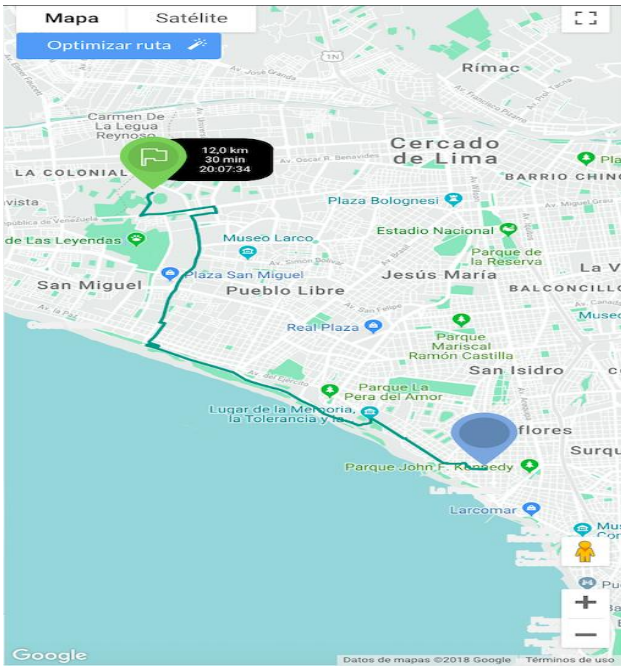

Fig. 7. Graphical interface of the web system to visualize the route.

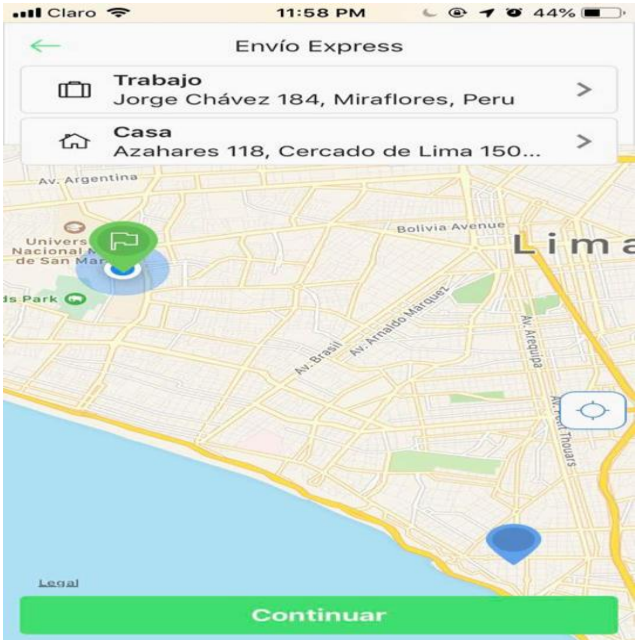

Fig. 8. Graphical interface of the mobile application

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IV. RESULTS AND DISCUSION

In this section, the results obtained from the training carried out with the test data entered into the system are presented. The output obtained in the "Fully connected Layer" is what serves as a response to verify the degree of accuracy of the system after a certain amount of learning cycles.

Training patterns

To validate the model, the data was used from a delivery services company dedicated to the delivery of different products in the city of Lima, Peru, 800 records of deliveries were taken, of which 200 have been separating for testing, each record with seven input parameters: latitude, longitude, number, task, day, hour and minute respectively. Table II shows the range of values that can be taken for each training pattern.

TABLE III. TRAINING PATTERNS

Pattern	Range	Example value
Latitude	Coordinate range within Lima (-12)	-12.057213
Longitude	Coordinate range within Lima (-77)	-77.080063
Number	It depends on the number of orders of the same product	5
Task	If it is delivery = 1 If it is pickup = 0	1
Day	Day>0 andDay<=30	15
Hour	Hour>=0 andHour<24	15
Minute	Minute>=0 and Minute<60	30

Neural network validation

The proposed model has been trained with 800 data, then it has been tested to verify the accuracy, entering the data from table IV as input.

TABLE IV. EXPECTED RESULTS

	Pattern	E.R
1	-12.074150,-77.079642,3,1,8.0,22.0,52.0	23.0,22.0,0.0,30.0
2	-12.080688,-77.091532,2,0,8.0,22.0,52.0	23.0,25.0,0.0,33.0
3	-12.074150,-77.079642,1,1,8.0,22.0,52.0	23.0,15.0,0.0,23.0
4	-12.084890,-77.094946,2,0,8.0,22.0,12.0	22.0,57.0,0.0,45.0
5	-12.107192,-77.022271,1,1,8.0,22.0,12.0	23.0,30.0,1.0,18.0
6	-12.116834,-77.032012,3,1,8.0,22.0,12.0	22.0,27.0,0.0,15.0
7	-12.123681,-77.037073,2,0,8.0,22.0,12.0	22.0,20.0,0.0,8.0
8	-12.116834,-77.032012,1,1,8.0,22.0,12.0	22.0,22.0,0.0,10.0
9	-12.078984,-77.081906,2,0,8.0,21.0,55.0	22.0,10.0,0.0,15.0
10	-12.118971,-77.037654,2,0,8.0,21.0,48.0	21.0,53.0,0.0,5.0
11	-12.095829,-77.059799,3,1,8.0,21.0,36.0	21.0,56.0,0.0,20.0
12	-12.092442,-77.065691,2,0,8.0,21.0,36.0	21.0,46.0,0.0,10.0
13	-12.095829,-77.059799,1,1,8.0,21.0,36.0	21.0,45.0,0.0,9.0
14	-12.095829,-77.059799,3,1,8.0,21.0,20.0	22.0,0.0,0.0,40.0
15	-12.080583,-77.107701,2,0,8.0,21.0,20.0	22.0,30.0,1.0,10.0
16	-12.095829,-77.059799,1,1,8.0,21.0,20.0	21.0,50.0,0.0,30.0
17	-12.095829,-77.059799,3,1,8.0,21.0,15.0	21.0,20.0,0.0,5.0
…	..	…
188	-12.096201,-77.069232,2,0,8.0,21.0,15.0	21.0,33.0,0.0,18.0
199	-12.115970,-77.024624,3,1,8.0,21.0,11.0	21.0,47.0,0.0,36.0
200	-12.121792,-77.020445,2,0,8.0,21.0,11.0	21.0,16.0,0.0,5.0

The data has been represented as follows:

Pattern = {lt,lg,n,t,d,h,m}

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Where: lt = Latitude, lg = Longitude, n = number, t = task, d = day, h = hour, m = minute

TABLE V. TEST RESULTS

	Pattern	R.O
1	-12.074150,-77.079642,3,1,8.0,22.0,52.0	23.0,22.0,0.0,30.0
2	-12.080688,-77.091532,2,0,8.0,22.0,52.0	23.0,42.0,0.0,50.0
3	-12.074150,-77.079642,1,1,8.0,22.0,52.0	23.0,25.0,0.0,33.0
4	-12.084890,-77.094946,2,0,8.0,22.0,12.0	5.0,25.0,7.0,13.0
5	-12.107192,-77.022271,1,1,8.0,22.0,12.0	6.0,14.0,8.0,2.0
6	-12.116834,-77.032012,3,1,8.0,22.0,12.0	22.0,47.0,0.0,35.0
7	-12.123681,-77.037073,2,0,8.0,22.0,12.0	22.0,39.0,0.0,27.0
8	-12.116834,-77.032012,1,1,8.0,22.0,12.0	22.0,27.0,0.0,15.0
9	-12.078984,-77.081906,2,0,8.0,21.0,55.0	22.0,35.0,0.0,40.0
10	-12.118971,-77.037654,2,0,8.0,21.0,48.0	21.0,55.0,0.0,7.0
11	-12.095829,-77.059799,3,1,8.0,21.0,36.0	22.0,0.0,0.0,24.0
12	-12.092442,-77.065691,2,0,8.0,21.0,36.0	21.0,54.0,0.0,20.0
13	-12.095829,-77.059799,1,1,8.0,21.0,36.0	21.0,46.0,0.0,10.0
14	-12.095829,-77.059799,3,1,8.0,21.0,20.0	22.0,30.0,1.0,10.0
15	-12.080583,-77.107701,2,0,8.0,21.0,20.0	22.0,10.0,0.0,50.0
16	-12.095829,-77.059799,1,1,8.0,21.0,20.0	21.0,20.0,0.0,0.0
17	-12.095829,-77.059799,3,1,8.0,21.0,15.0	21.0,35.0,0.0,20.0
…	..	…
188	-12.096201,-77.069232,2,0,8.0,21.0,15.0	21.0,30.0,0.0,15.0
199	-12.115970,-77.024624,3,1,8.0,21.0,11.0	21.0,51.0,0.0,40.0
200	-12.121792,-77.020445,2,0,8.0,21.0,11.0	21.0,21.0,0.0,10.0

As can be seen, the RO column does not give an accuracy of 82.7%, these results are contrasted with other investigations.

In research [1], the authors used the Bing map service together with the Dijkstra algorithm to calculate the delivery distance from one point to another, comparing in this work we make use of Google maps services, our proposal is based on developing our own delivery route prediction service using a GAN model and a CNN structure, avoiding the high costs of using a map service.

In [6], the researchers took into account the departure time and the human factor as important research variables, unlike our service which takes latitude, longitude, hour and minute in which the order was placed as important attributes. In our service, these attributes allow us to accurately approximate the time it will take and the approximate time the order will arrive at the destination.

In [7], they used the LSTM network to approximate the delivery time that only one order will have. In our work we use our GAN model and the CNN structure to estimate the delivery times of each product, whether of the same or of a different type, delivering in a single route all the products of the same type, using the approximate delivery time as a guide.

Compared to [11], we use queue parallelization for different products and for each order for the same product, a delivery order number is assigned, and then we calculate the delivery time from the point where the previous delivery ended, respecting the order of arrival of the order and delivering all the orders of the same type in a single route.

CONCLUSIONS

In this research, we propose a deep learning model that calculates the time required for each delivery accurately based on the data of the registered orders. We also designed a hybrid approach that contains the components: deep feature learning, feature adaptation and classification. The results of the computational experiments show that the proposed model reached an accuracy percentage of 82.7%.

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