RESIDUAL MULTI-LAYERED PERCEPTRON DESIGN AND ANALYSIS

Abstract

The latest advances in technology have made it possible for the food sector to create more food in less time, which has a multiplicative impact on the ability of the business to make a profit. In this study, all pertinent context is included in a thorough literature analysis of prior studies on the use of machine learning and AI in the food business. To adequately depict the distinctive qualities connected to each eating place, we use nested feature groups. For every order that has the current dish listed among the dish- and restaurant-related variables, we compute the forecast. The outcomes demonstrate the efficacy of our method and the potential for further improvement by adjusting the MLP model utilising residual model precision.

Keywords: Machine Learning, Residual Learning, Food Processing Time, Food Orders.

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I. INTRODUCTION

The growth of any nation economy is impossible to imagine without the contributions that are made by the food business [1]. It is also important to the growth of the economy, both on a national and a global scale, and it plays a significant role in both of these. As a direct result of this, there is an immediate need for advancements to be made, not only in the quality of food products, but also in the safety of the transportation of those food products. In the most recent decades, artificial intelligence (AI) and various other cutting-edge technologies have been successfully implemented in order to accomplish this objective [2].

It is of the utmost significance to investigate the applications of AI in forward-thinking agriculture and the food industry. Procedures of this kind ensure that high-quality products will be delivered on time, while also meeting the demands that society places on its institutions. The food industry is now able to produce a greater quantity of food in a shorter amount of time thanks to the assistance of these innovative technologies, which has a multiplicative effect on the company ability to turn a profit [3].

Nearly every field of research and development in technology at the moment makes use of systems that are either completely self-sufficient or that are dependent on artificial intelligence. This paves the way for the computerization of the food business as well as the transformation of products [4]. Seed selection, crop monitoring, temperature monitoring, and watering monitoring are just a few of the areas that can benefit from a computerized system, which enables the food business to examine and expand upon the conditions that are most favorable [5].

The applications of artificial intelligence are not limited to the ones that have been mentioned here; there are many more. The preparation, warehousing, and transportation of culinary products can all be improved through the application of this substance. In order to achieve the objective of lowering the costs associated with the acquisition of packaging materials [6], it is possible that the application of other high-tech tools, such as robots and aircraft that fly themselves, will be of assistance. It will be useful for transporting food stuffs, dealing with potentially dangerous circumstances, and producing high-quality products [7].

In the food industry, the most essential functions of artificial intelligence can be broken down into two primary categories: the management of food security and the management of food quality. In addition to that, there is a third division, which is the administration of food safety. This study presents a comprehensive literature analysis of previous research pertaining to the application of machine learning and AI in the food industry, including all relevant context. [8].

The implementation of machine learning (ML) can be beneficial to a number of aspects of decision-making, including the process of selecting transportation routes, the availability of raw materials, the estimation of future demand, and the planning of logistics [9]. Machine learning can be of assistance with delivery route issues by synchronizing the agent position with current and future traffic conditions to determine the best route, and then notifying the agent of it. This can be helpful with resolving issues related to delivery routes [10].

Consistent orders can be completed with less hassle and fewer issues if the delivery process is streamlined and reliable, such as when there is a shortage of delivery employees or when packages arrive late. Because of this, it is now feasible to promptly fulfill a greater number of orders [11].

Incorporating ML also results in a bigger data collection over time, which can be evaluated using additional AI-based algorithms to create a smarter system. This evaluation can be done in order to make the system more efficient. Increasing the level of intelligence possessed by the system is one way to accomplish this goal. In order to gain a competitive advantage over other companies, it may be beneficial to make use of more advanced AI-based techniques such as deep learning (DL) when performing an analysis of this kind.

In this study, we investigate how the FPT of the current transaction adapts in real time to meet the growing demand at the restaurant. We collect information on the volume of orders received as well as the amounts of time spent waiting for couriers in addition to calculating the prediction of orders that have previously been placed.

II. RELATED WORKS

These restaurants now have access to a new method because there are online platforms that enable them to outsource food delivery services (FDS), which were previously supplied by the restaurants themselves through the employment of drivers. As a result of the availability of these online platforms, these restaurants now have access to the new method [12]. The FDS efforts should be centered on tracking the amount of time it takes to transport meals to customers, as this should be their primary concern [13]. Following the placement of an order by a customer, it should not take more than an hour and a half for that customer to receive their purchase, provided that everything goes according to plan. It is not necessary to spend an exorbitant amount of money on labor or transportation-related means in order to make such a deadline [14].

The primary advantage of using the service is that it allows customers to place their product purchases over the internet, which is much more convenient than any other method. Online shopping has grown in popularity and is now more widely accepted in societies where people place a higher value on their own time and where customers place a higher importance on features that save them time [15]. It is not possible to accomplish this objective without accurate forecasts of future demand and an efficient administration of all available resources. When things are difficult, it would be a disaster for both the service and the people who use it if it ran out of possibility as a result of an increase in the number of orders. This would be especially true in situations where things are difficult. As a direct result of this, shipping delays have become a primary problem for a good deal of FDS businesses [16].

It is possible that customers will become frustrated and develop an unfavorable opinion of the meal delivery service if their orders are not delivered within the allotted amount of time. When a customer order is late, getting delivery service likely to be less. In addition, they are more likely to leave negative comments and offer poor ratings when they do use the service [17].

When the customer actual arrival time takes longer than what was guaranteed, it is common practice for them to express their irritation over the violation of contract. A

restriction is anything that places a ceiling on the system as a whole and its potential for growth as a whole. In order to obtain an in-depth comprehension of the complete process, it is necessary to dismantle the procedure into its component parts. The next thing that needs to be done is to make an estimate of how long it will take to finish each of the individual stages that comprise the procedure [18].

According to the conclusions of the study [19] enhancing the Ready to In-Transit procedure leads to a significant improvement in the overall quality of the food transportation process. By having the optimal amount of riders at the optimal time, the procedure can be made to be more efficient. Instruments for forecasting have been utilized in a large number of studies that cover a wide variety of academic fields. Workforce management (WFM), is a method that is increasingly used in contact centers to handle employee scheduling and scheduling of shifts for employees. WFM can be subdivided into a variety of processes, such as shift scheduling, and forecasting, amongst others. The WFM methodology can be seen in both of these subprocesses.

The use of integer programming (IP) algorithms [20], which are one of the most prevalent theoretical and algorithmic approaches, is restricted to situations in which the total number of employees has already been determined. In addition, the outcomes predicted by conventional queuing models and the outcomes actually observed are very different from one another. It is possible to use simulation models, which are also the simplest method, in order to determine the staffing requirements that are required in order to accomplish the level of service that is desired. This is something that can be done in order to achieve the degree of service that is desired.

III. PROPOSED METHOD

Figure 1 is a diagram that illustrates the purchasing and delivery procedures that are typical of meal delivery platforms. An order is placed by a consumer through the platform, the restaurant will be notified, and the platform will collaborate with the delivery service to coordinate the dispatch of the order. Once the establishment has finished preparing the food and the courier has delivered the finished product to the customer doorstep, the request will be considered fulfilled.

An important component of the system is a module that can compute an estimate of the amount of time it will take a restaurant to prepare an order from the point at which the restaurant receives the order until the point at which it is ready to be picked up by a courier. This estimate can be used to determine when the order is ready to be picked up. The Food Processing Time (FPT) is generally responsible for approximately 30% of the total cycle time that is spent fulfilling orders in a food delivery network.

The logistics of the system are intended to ensure that transport personnel appear at eateries precisely when customers place their orders for food. This is done to avoid any unnecessary delays. If the couriers appear at the location too early, their overall transportation experience will suffer as a result because they have other orders that will be delayed as a result of their early arrival. This is due to the fact that the delivery people will have to wait for a considerable period of time. For the time being, customers would prefer that their orders not be picked up and delivered to them too late for reasons having to do with the quality of the cuisine. In this regard, customers would prefer that their orders not be picked up and

delivered to them too late. Therefore, it is important to ensure that an accurate estimate of the FPT is provided for each transaction in order to make sure that both the customer and the Courier are satisfied with the service.
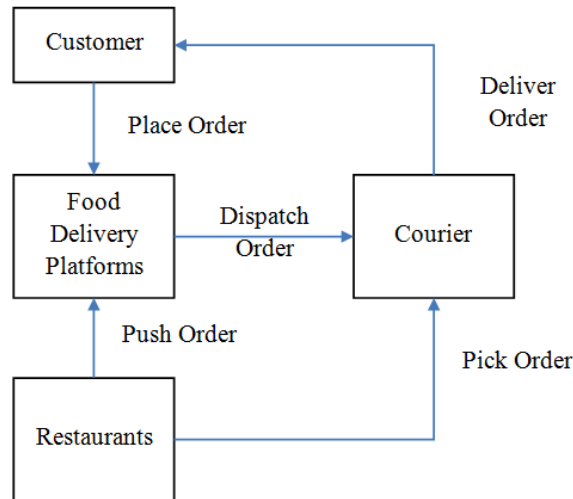
Figure 1: Food Delivery Using ML

1. **Feature Extraction:** It is important to extract features in order to generate sharp distributions, which are superior to unsharp distributions in terms of the amount of information they provide that can be used for decision-making.

   - **Context Features:** There are times that are periodic in character, and these time periods are associated with services that deliver food on demand. We are able to derive an approximation of the mean FPT by utilizing orders that were placed at a variety of periods throughout the day and on days of the week as well as weekends.

     As a result of the lengthier wait times that occur during peak hours, restaurants typically require more time to prepare the meals that they serve their customers. In addition to the different periods, FPT shifts throughout the week as well, particularly between Monday and Friday, as well as between Saturday and Sunday.

     Outside of normal business hours, the most purchases are typically placed by customers during the weekend. This is because customers have more time on their hands. The fact that the two forms are comparable to one another demonstrates that the occurrence did, in fact, take place.

     With the help of the information that was just presented, we have the ability to derive two context characteristics. The day of the week and the time of day, broken down into 10-minute increments, are the elements that make up these context characteristics. Both of these context characteristics are utilized in the process of FPT prediction in order to capture the time periodicity

   - **Restaurant Features:** We construct a number of nested feature groups in order to effectively represent the one-of-a-kind characteristics that are associated with each eating establishment.

- **Basic Information:** It is acceptable to use a restaurant phone number as an identifier in order to keep track of the uniqueness of the establishment. In addition, the accompanying portion provides a description of the primary types of food that each restaurant specializes in preparing, such as refreshment, dessert, dumplings, or destination cuisine. There is a substantial amount of difference between the various kinds in terms of the total amount of time that is required to prepare them as well as the strategy that is utilized. After selecting a few representative examples of the most prevalent categories of dining establishments, we proceed to compute the prediction of orders placed in those establishments.

- **Supply and Demand Information:** There is a significant amount of downtime associated with the FTP of a transaction because it necessitates waiting on the completion of orders that came before it. This causes the transaction to wait on the completion of orders. The current supply and demand conditions at the restaurant have a substantial impact on the FPT order that should be placed. It is notoriously challenging to make accurate predictions about the conditions of supply and demand.

  We use the number of orders that an establishment has received in the last ten to thirty minutes as a stand-in for the current demand that is being placed by customers. This number can range anywhere from 0 to 100. The supply and demand dynamics in the industry are reflected in the standard wait time that is expected of restaurant messengers. In this study, we investigate how the FPT of the current transaction adapts in real time to meet the growing demand at the restaurant. Specifically, we look at how the FPT adjusts to meet the demand for larger portions.

- **Historical Statistics:** It is often essential to look back in time in order to make improvements to regression models in practice; this is where historical statistics come into play. We collect information on the volume of orders received as well as the amount of time spent waiting for couriers in addition to calculating the prediction of orders that have previously been placed at the restaurant. These statistics are the same as data on supply and demand in real time, and they are utilized in the same manner. We combine orders that have been placed within the most recent two weeks, on the same workday within the most recent four weeks, and for the most recent and upcoming timeframes on each day within the most recent two weeks. This allows us to collect data at a variety of temporal resolutions.

2. **Dish Features:** When placing an order, it is essential to keep in mind that the order will consist of several different dishes, each of which will have its own number, and that the restaurant will need to prepare sufficient portions of each dish in order to fulfill the order in its entirety. Keeping these things in mind will help ensure that the restaurant is able to successfully complete the order.

- **Basic Information:** To commence, some background information is in order: The quantity of food that is served in addition to the cost of each individual dish are the primary factors to take into consideration. Since the total quantity of dishes is something that should have an effect on the FPT, it is logical to assume that the FPT will change depending on this factor. In the kitchen, it is possible to prepare multiple dishes of the same kind at the same time the majority of the time; however, there may

be times when there are delays that were not anticipated. The prices of dishes have significance because more time and effort are typically necessary to prepare more expensive meals, which makes the preparation processes more difficult. As a result, the prices of dishes reflect these factors. Because we do not have information regarding the FPT of the individual dishes, we must determine the prediction of orders that include the dinner at a variety of price points in order to accommodate our customers.

- **Supply and Demand information:** We also keep track of the number of times that a particular meal has been purchased in the past. This is done in the same manner as the real-time features described above. This information was derived from the records that we keep. Because dishes that are very similar can be prepared at the same time, this is important because it can cause customers to wait in line for a noticeably longer period of time.

- **Historical Statistics:** Every single dinner that is provided does not permit access to the FPT. This policy is consistently enforced. In order to accomplish this, we calculate the prediction for all orders that have included the present dish as one of the dish-related features at the same granularity as the restaurant features. This takes into account all of the features that are related to the dish. This is carried out for each and every transaction individually.

3. **Feature Processing:** The information about the establishment characteristics as well as the contextual information are both encoded together, and then the characteristics of the dish themselves are displayed. Because we are representing the features with residual RDF, we are able to take into account both the low-order and the high-order feature relationships. This is made possible by the fact that we are representing the features.

$v_{cr} = DCN(X_c;X_r),$
$v_d = DCN(X_d), d \in D,$

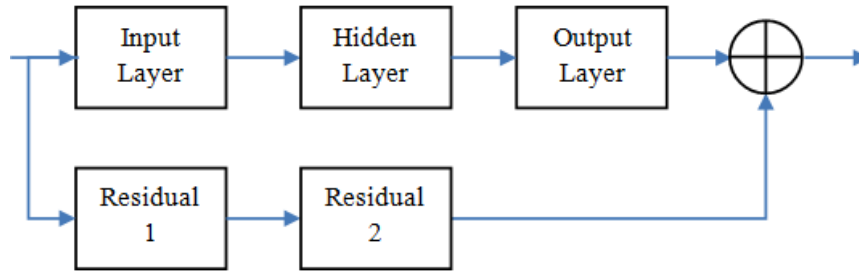where
X_c - context features,
X_r - restaurant features and
X_d - dish features d.

The context and restaurant characteristics, abbreviated as v_{cr}, and the food characteristics, abbreviated as v_d, are both k-dimensional vector representations that are acquired through preprocessing.

IV. FORECAST USING RESIDUAL MLP

MLP is a type of neural network, employs a form of supervised learning called back-propagation to train its neurons. This contributes to the network general performance being improved. An MLP should have three levels for optimal performance, as shown in Figure 2: an input layer, a hidden layer or layers, and an output layer or layers, with each neuron in one layer linked to all of the neurons in the next layer. The layers should be in this order: an input layer, a hidden layer or layers, and an output layer or layers. A MLP should consist of three

levels: an input layer, a hidden layer or layers, and an output layer or layers. There has been a lot of discussion about how valuable MLP can be when it comes to the resolution of non-linear issues.

Figure 2: Architecture of Residual MLP

The equation depicts the relationship that exists between the variables of the outcomes, the values of the bias, and the factors that went into producing the outcomes.

$$S_i = \sum_{i=1}^{n} w_{ij} I_i + \beta_i \tag{1}$$

where
I - input layer,
I_i - input variable i,
n - total inputs,
βj - bias, and
ω_{ij} – link weight at a level j.

The sigmoid function, which can be found by solving Equation (2), is frequently employed as an activation function in the MLP, which stands for multilayer perceptron.

$$f_j = \frac{1}{1 + e^{-S_j}} \tag{2}$$

where,
S - activation function.
The performance of the model can be evaluated by comparing the actual values achieved by the model with the intended values:

$$y_i = f_i \left(\sum_{i=1}^{n} w_{ij} I_i + \beta_i \right) \tag{3}$$

where,
y - output of MLP.
The performance of the model can be judged based on how closely the actual values match the intended values. 80% of the data was used in the training of the MLP, and the algorithm that was used to structure this data has done so in a manner that is completely arbitrary. Training the model with varying numbers of hidden-layer neurons, ranging from 10 to 18 at intervals of 4, enabled for the best potential architectural layout of the

prediction model to be determined. Because it demonstrated better performance than the other options, the Tanh (x) activation function was chosen as the best option.

V. RESULTS AND DISCUSSIONS

In this part of the report, we evaluate how successful our approach was and come to some conclusions about how it could be made even better. The root-mean-square error (RMSE), and R^2 determination coefficient, are two of the metrics that are used when evaluating MLP and ANFIS in terms of their predictive ability and accuracy. Both of these metrics are abbreviated as RMSE and R^2, respectively.

$$\text{RMSE} = \frac{1}{N} \sum_{i=1}^{N} (A - P)^2 \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (A - P)^2}{\sum_{i=1}^{n} (A)^2} \tag{5}$$

where
A - target values,
P - predicted values, and
N - data.

It is feasible to evaluate the accuracy of a number of different models by making use of these various metrics of success. In this particular study, 70% of the data was utilized for the training of the models, and the model that exhibited the highest degree of forecasting ability was selected as the winning model. After the models had been trained on seventy percent of the data that was accessible, the accuracy of the models was evaluated by computing the RMSE and the R^2.

- **Dataset:** Food delivery Dataset [21] is used in the study and when a customer places an order for food delivery with a restaurant, grocery store, or third-party delivery service, the customer is supported by a courier service. The most common methods to place an order are either through the establishment where the food will be prepared, such as a restaurant or grocery store, or through a third-party organization that will be in charge of coordinating the delivery of the food.

  Meals, beverages, condiments, and desserts, as well as groceries, can all be delivered straight to your door in convenient plastic bags, and this includes grocery shopping. These receptacles are available for use in the process of transporting the items. The individual who is making the transport will typically use a vehicle; however, in more heavily populated urban areas, where residences and restaurants are situated closer to one another, bikes or motorized scooters may be used instead of vehicles.
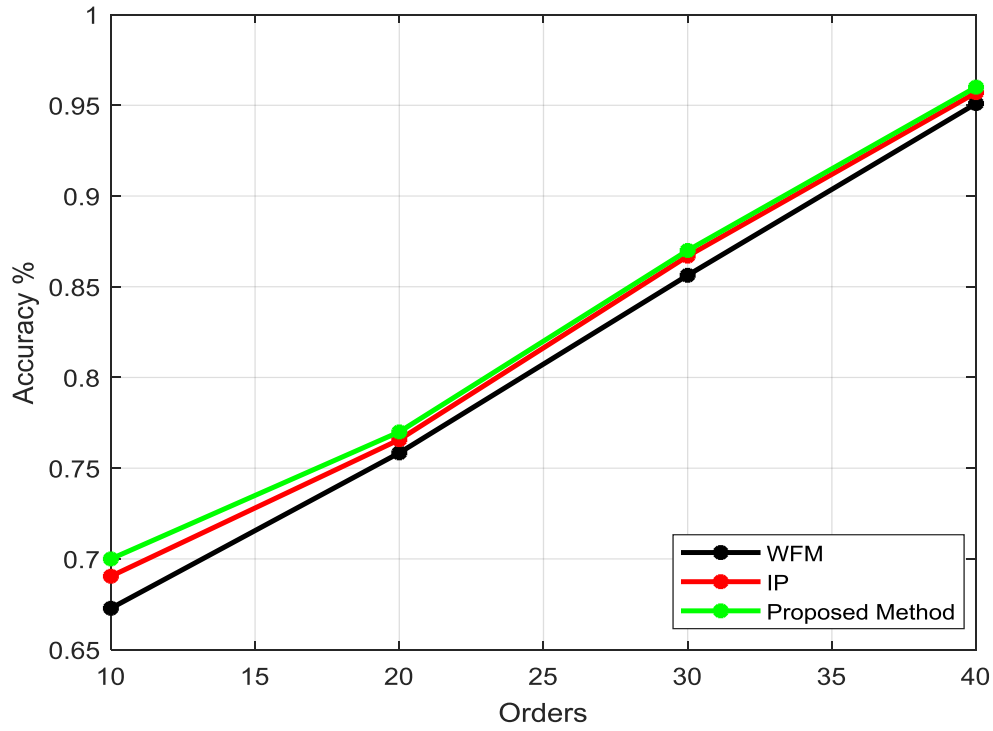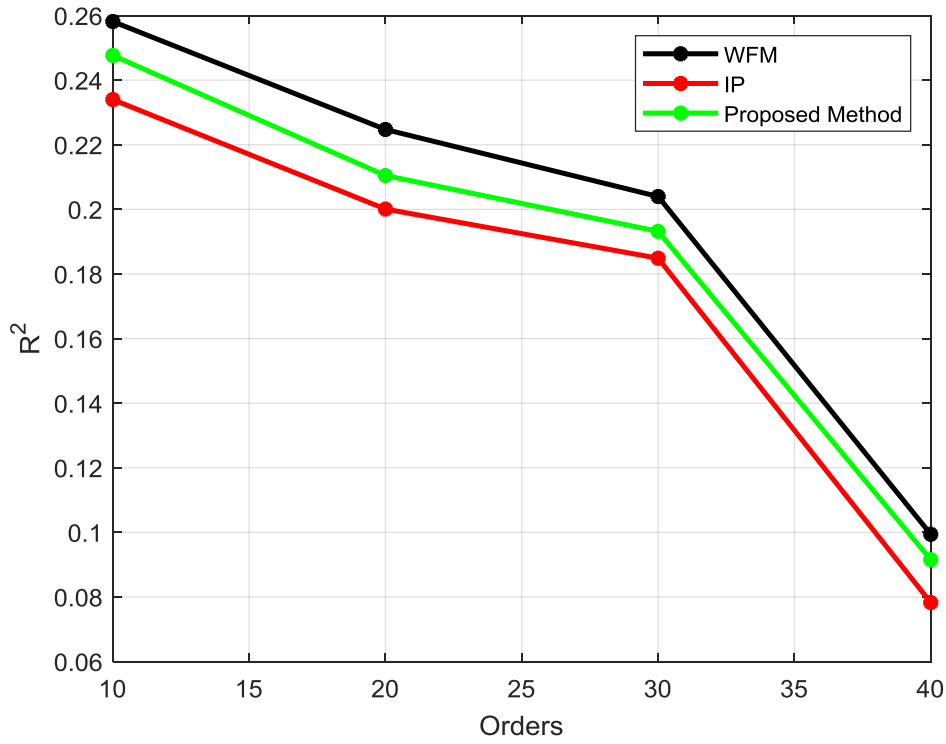
Figure 3: Prediction Accuracy
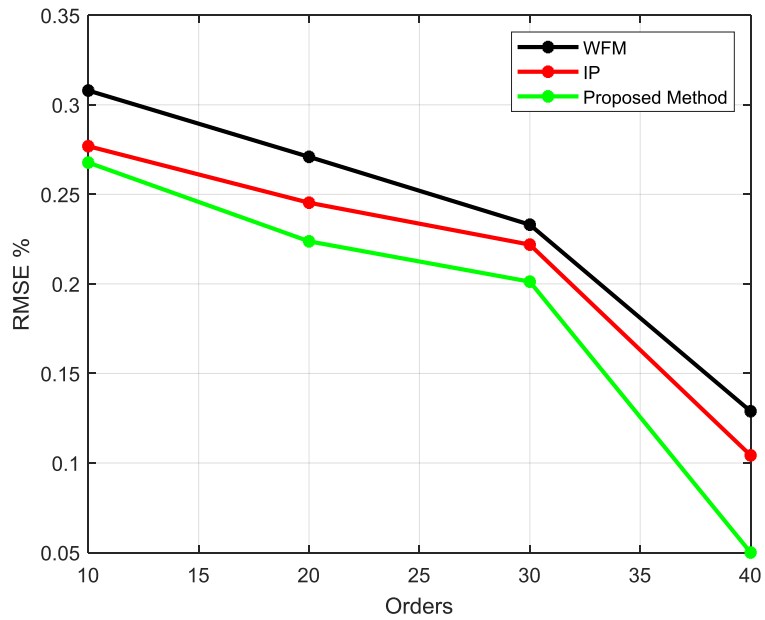
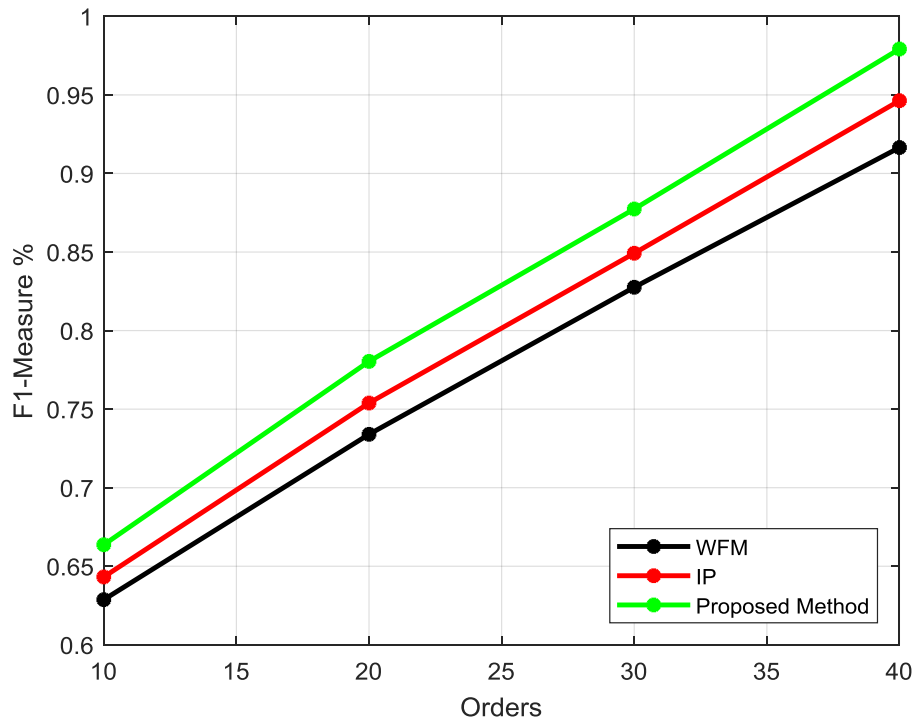**Figure 4**

Figure 5: R^2

Figure 6: F1-Measure

As in Figure 3-6, the algorithms are trained using approximately 80% of the data that is available to them. During the process of training each model, we gave it a new supply of neurons and made it go through its exercises thrice. In total, the operation took about an hour. It is possible to fine-tune the MLP model using residual model precision in order to determine the ideal number of neurons to use. When it came to making predictions regarding meal delivery based on the information that was extracted, the model that consisted of 10 neurons performed the best at this point in time. This was demonstrated by a decrease in the corresponding RMSEs, which are a precision measurement tool for the predictions.

VI. CONCLUSIONS

In this research, we investigate how the FPT of the current transaction adapts in real time to meet the growing demand at the restaurant. We collect information on the volume of orders received as well as the amounts of time spent waiting for couriers in addition to calculating the prediction of orders that have previously been placed at a restaurant. The accuracy of the models was evaluated by computing the RMSE and the R^2. From the results, it is seen that the proposed method achieves higher rate of accuracy and reduced prediction errors than the existing methods.

REFERENCES

[1] Chai, J., Zeng, H., Li, A., & Ngai, E. W. (2021). Deep learning in computer vision: A critical review of emerging techniques and application scenarios. Machine Learning with Applications, 6, 100134.
[2] Srinivas, T., Aditya Sai, G., & Mahalaxmi, R. (2022). A Comprehensive Survey of Techniques, Applications, and Challenges in Deep Learning: A Revolution in Machine Learning. International Journal of Mechanical Engineering, 7(5), 286-296.
[3] Tan, R. Z., Chew, X., & Khaw, K. W. (2020). Quantized deep residual convolutional neural network for image-based dietary assessment. IEEE Access, 8, 111875-111888.
[4] Perugachi-Diaz, Y., Tomczak, J. M., & Bhulai, S. (2021). Deep learning for white cabbage seedling prediction. Computers and Electronics in Agriculture, 184, 106059.
[5] Kumar, S., & Shah, A. (2021). Revisiting food delivery apps during COVID-19 pandemic? Investigating the role of emotions. Journal of Retailing and Consumer Services, 62, 102595.
[6] Gupta, V., & Duggal, S. (2021). How the consumer's attitude and behavioural intentions are influenced: A case of online food delivery applications in India. International Journal of Culture, Tourism and Hospitality Research, 15(1), 77-93.
[7] Wen, H., Pookulangara, S., & Josiam, B. M. (2022). A comprehensive examination of consumers' intentions to use food delivery apps. British Food Journal, 124(5), 1737-1754.
[8] Alalwan, A. A. (2020). Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. International Journal of Information Management, 50, 28-44.
[9] Kaur, P., Dhir, A., Talwar, S., & Ghuman, K. (2021). The value proposition of food delivery apps from the perspective of theory of consumption value. International Journal of Contemporary Hospitality Management, 33(4), 1129-1159.
[10] Cho, M., Bonn, M. A., & Li, J. J. (2019). Differences in perceptions about food delivery apps between single-person and multi-person households. International Journal of Hospitality Management, 77, 108-116.
[11] Ray, A., Dhir, A., Bala, P. K., & Kaur, P. (2019). Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. Journal of Retailing and Consumer Services, 51, 221-230.
[12] Sharma, R., Dhir, A., Talwar, S., & Kaur, P. (2021). Over-ordering and food waste: The use of food delivery apps during a pandemic. International Journal of Hospitality Management, 96, 102977.
[13] Belanche, D., Flavián, M., & Pérez-Rueda, A. (2020). Mobile apps use and WOM in the food delivery sector: the role of planned behavior, perceived security and customer lifestyle compatibility. Sustainability, 12(10), 4275.
[14] Belanche, D., Flavián, M., & Pérez-Rueda, A. (2020). Mobile apps use and WOM in the food delivery sector: the role of planned behavior, perceived security and customer lifestyle compatibility. Sustainability, 12(10), 4275.

[15] Troise, C., O'Driscoll, A., Tani, M., & Prisco, A. (2021). Online food delivery services and behavioural intention–a test of an integrated TAM and TPB framework. British Food Journal, 123(2), 664-683.

[16] Sun, P. (2019). Your order, their labor: An exploration of algorithms and laboring on food delivery platforms in China. Chinese Journal of Communication, 12(3), 308-323.

[17] Xu, X., & Huang, Y. (2019). Restaurant information cues, Diners' expectations, and need for cognition: Experimental studies of online-to-offline mobile food ordering. Journal of Retailing and Consumer Services, 51, 231-241.

[18] Prasetyo, Y. T., Tanto, H., Mariyanto, M., Hanjaya, C., Young, M. N., Persada, S. F., ... & Redi, A. A. N. P. (2021). Factors affecting customer satisfaction and loyalty in online food delivery service during the COVID-19 pandemic: Its relation with open innovation. Journal of Open Innovation: Technology, Market, and Complexity, 7(1), 76.

[19] Cai, R., & Leung, X. Y. (2020). Mindset matters in purchasing online food deliveries during the pandemic: The application of construal level and regulatory focus theories. International Journal of Hospitality Management, 91, 102677.

[20] Hwang, J., Lee, J. S., Kim, J. J., & Sial, M. S. (2021). Application of internal environmental locus of control to the context of eco-friendly drone food delivery services. Journal of Sustainable Tourism, 29(7), 1098-1116.

[21] Food Delivery Dataset | Kaggle, https://www.kaggle.com/datasets/gauravmalik26/food-delivery-dataset, Available on 25.02.2023.