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RESTAURANT DENSITY PREDICTION SYSTEM USING FEED FORWARD NEURAL NETWORK

Muhammad Kurnia Sandi [1*)] , Anggunmeka Luhur Prasasti [2], Marisa W. Paryasto [3]

Computer Engineering
Telkom University
https://telkomuniversity.ac.id
muhammadkurniasandi@student.telkomuniversity.ac.id [1], anggunmeka@telkomuniversity.ac.id [2]
marisaparyasto@telkomuniversity.ac.id [3]

(*) Corresponding Author

Abstrak

Pada zaman sekarang, informasi mengenai suatu hal begitu penting. Tingkat kepercayaan masyarakat modern bergantung pada keterujian suatu informasi. Informasi yang teruji dan akurat akan memberikan dampak yang baik bagi masyarakat banyak. Salah satu informasi yang penting namun sering di lewatkan adalah informasi mengenai kepadatan suatu restoran. Informasi mengenai kepadatan restoran penting untuk diketahui karena dapat mempengaruhi tindakan dari seseorang yang akan mengunjungi restoran tersebut. Informasi ini juga berguna untuk memberi informasi lebih awal agar pengunjung menghindari restoran yang penuh untuk menghindari penyebaran virus Covid-19, dan beberapa hal lainnya. Dengan dibatasinya jam operasi juga jumlah pengunjung restoran, informasi mengenai kepadatan suatu restoran menjadi sangat dibutuhkan. Tidak adanya informasi kepadatan restoran menjadi masalah utama pada masyarakat. Adanya kebutuhan masyarakat tersebut, membuat penelitian ini bertujuan untuk memprediksi kepadatan suatu restoran satu jam kemudian. Didasari data survei dan data literatur yang ada, dengan metode simulasi dan juga analisis sistem yang dibangun menggunakan arsitektur kecerdasan buatan Feedforward Neural Network lalu dilatih dengan algoritma Backpropagation menghasilkan akurasi sebesar 97.8% dengan data literatur.

Kata kunci: Kepadatan Restoran, Kecerdasan Buatan, Feedforward Neural Network, Time Series Forecasting.

Abstract

In this day and age, information about something is so important. The level of trust of modern society depends on the testing of information. Tested and accurate information will have a good impact on the community. One of the important but often missed information is information about the density of a restaurant. Information about restaurant density is important to know because it can affect the actions of someone who will visit the restaurant. This information is also useful to provide information in advance so that diners avoid full restaurants to avoid the spread of the Covid-19 virus, among other things. With limited operating hours as well as the number of restaurant visitors, information about the density of a restaurant becomes much needed. The lack of information on restaurant density is a major problem in the community. The needs of the community, made this study aims to predict the density of a restaurant an hour later. Based on survey data and existing literature data, with simulation methods and also system analysis built using feedforward neural network artificial intelligence architecture and then trained with Backpropagation algorithms produced an accuracy of 97.8% with literature data.

Keywords: Restaurant Density, Artificial Intelligence, Feedforward Neural Network, Time Series Forecasting.

INTRODUCTION

In this modern era, many emerging restaurant businesses from regional food to overseas. The rise of these restaurants is particularly prevalent in big cities (Richard, 2019). The emerging restaurants invite the appeal of the community because in addition to being a place to enjoy food restaurants are also often used to gather with friends. Besides, the existence of free WIFI service makes visitors feel at home lingering inside the restaurant resulting in a pile of restaurant visitors (Wardani, Jumain, & Mufarihin, 2020). The appeal of visitors to the restaurant is very varied. From those who are willing to queue to reluctant to queue. Lack of information about the density of restaurants to go to can make visitors who are reluctant to queue and have already come to the restaurant feel disappointed (Fadhillah, Kharisma, & Afirianto, 2020). As a result, diners have to look back for other restaurants. But it is very detrimental because it is also possible that the restaurant that suits the customer's wishes is far from the previous restaurant.

Solutions such as ordering food at restaurants using the delivery service can be used to avoid full restaurants and long wait times (Chen, Hu, & Wang, 2019). This service allows customers to simply stay in place and the service owner will deliver pre-ordered food. But sometimes this service has a fairly long estimated time and is not as expected (Chen et al., 2019). Factors such as traffic congestion and length of wait times in restaurants make the food ordered not following the estimated time (Chen et al., 2019). Again the same factor that is the density of restaurants is the cause of the precisely estimated time of delivery service. In obtaining restaurant density information, technology in the form of mobile phone applications combined with artificial intelligence is very useful for visitors to know the density of the intended restaurant. This technology can also be used to prevent crowds in public places to prevent the spread of the Covid-19 virus.

Public places such as restaurants have become the places where the pandemic is spreading quite high (Qian et al., 2020; Sexton & Seaman, 2021), this is due to the needs of modern people who are accustomed to instant food. Based on these community needs, this study aims to help people in obtaining information on restaurant density to suppress the spread of pandemics. So in this case, we need a system to predict the state of a restaurant. In creating this system, artificial intelligence can be used to predict the state of a restaurant. By using existing data, artificial intelligence architecture, namely feedforward neural network, can easily be used to predict the density of a restaurant. After analyzing and conducting several simulations to predict the density of restaurants and get good results, the results of this system in the form of predicting restaurant density can be informed by various media to help the public in knowing the density of the intended restaurant.

In previous research (Fadhillah et al., 2020; Widjaya, Suryawan, & Stefani, 2014), there is no research as currently researched, but there are few similarities between calculating many customers, mealtimes, and income. This research will be better because it focuses more on finding the condition of the restaurant that is density. Later the results of density can be developed to determine the number of people, time in line, income, and others. But the limited data and technology available make this research limited only to large restaurant restaurants and users who use android phones with the latest operating system.

RESEARCH METHODS

1. Data Source

Data obtained from a coffee shop in January of 2020. The data used is hourly visitor data from 7 a.m. to 9 p.m. Dataset can be seen at the link https://github.com/sayahsorangan/Resfo.

2. Prediction System Design

There are several parameters in determining the condition of a place, such as the parameters used in determining population density (area and number of residents in the area), or parameters used in determining road conditions (many vehicles, vehicle speed, vehicle type, road area, and others). These parameters are implemented according to the environment to be reviewed. Restaurants have characteristics that intersect with the characteristics of roads or residential areas. In restaurants, variables change not as fast on the road, but not as late as in residential areas. So that the combination of parameters of the two places is required.

The first parameter is the day of the week. Every day for example with numbers such as Monday (1), Tuesday (2), and so on until Sunday (7). This parameter is useful for seeing trends every day in restaurants. The second parameter is opening hours. According to the data obtained in the journal. Opening hours at the restaurant under review start from 9:00 to 21:00. Just like the first parameter, it's useful to see trends every hour.

The third parameter is the capacity of the restaurant. This is based on the lack of places in restaurants that can be occupied. This parameter is closely related to the area to calculate the density of the population, which in restaurants also affects the number of servings available each day. As the area affects the density of the area, the capacity of this restaurant is key to predicting the density of restaurants (Christiani, Tedjo, & Martono, 2014; Thalib, 2018).

The fourth parameter is the number of diners in the restaurant. The number of visitors is the second most important parameter after capacity. This is because the number of visitors affects the density of restaurants such as the influence of vehicles on traffic, as well as the influence of the population on population density. These parameters may change over time (Christiani et al., 2014).

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The fifth parameter for predicting restaurant density is the average time of diners inside the restaurant. These parameters act like the effect of speed on traffic flow. In the event of a buildup or the average time, a high diner eats will be more crowded the restaurant (Thalib, 2018).

Feedforward Neural Network architecture created using five perceptrons on the input layer. The first input is parameter one (restaurant capacity), second is parameter two (number of restaurant visitors), third is parameter 3 (average time of restaurant visitors). At the input layer, each parameter will be normalized to zero to one vulnerable, with the following calculations (Akshay Kumar & Suresh, 2016; Auer, Burgsteiner, & Maass, 2008; Benzer, 2015; Berno et al., 2003; Frean, 1990; Grossi & Buscema, 2007; Hagan & Menhaj, 1994; Razavi & Tolson, 2011; Schmidt, Kraaijveld, & Duin, 1992; Whitley & Karunanithi, 1992; Wilamowski, 2011).

$$parameter\ 1 = \frac{day-1}{7-1} \quad (1)$$

$$parameter\ 2 = \frac{hour-10}{21-10} \quad (2)$$

$$parameter\ 3 = \frac{capasity}{capasity} \quad (3)$$

$$parameter\ 4 = \frac{people}{capasity} \quad (4)$$

$$parameter\ 5 = \frac{average\ time}{120} \quad (5)$$

In the hidden layer and output layer, the activation function to be used is the Sigmoid function, because the desired output is between zero and one. The sigmoid activation function can be calculated by the following formula.

$$Sigmod(x) = \frac{1}{1+e^{-x}} \quad (6)$$

The second and third hidden layers will consist of five perceptrons, then the output layer consists of one perceptron. So that the entire architecture of the Feedforward Neural Network can be seen as follows.

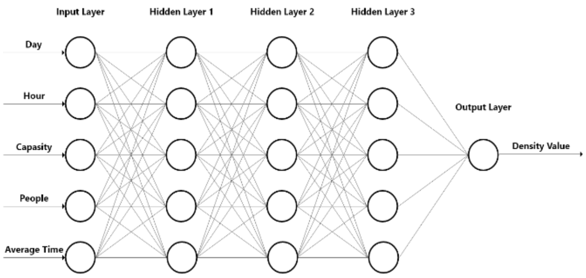


Figure 1. architecture Feedforward Neural Network.

This kind of architecture in Figure 1 is suitable because to predict things that change quickly, computing speed must be more important than good accuracy. But the expected accuracy is at least close to 80% to 90%. The balance in terms of accuracy and computing speed in terms of artificial intelligence is usually counterintuitive.

The output of this Feedforward Neural Network architecture is between zero and one. Being vulnerable to certain values means the restaurant is empty, medium, full, or very full. Vulnerable values can be seen in table 1.

Tabel 1. Output Classification

Vulnerable Value	Restaurant Conditions
Output <= 0.25	Empty
0.25 > Output <= 0.50	Medium
0.50 > Output <= 0.75	Full
0.75 > Output <= 1	Very Full

Backpropagation is used to search for the best W (weights), or smallest errors. Backpropagation is run a million times to get error levels close to zero. The weights in the first iteration will be initialized with random values. The error value of the output desired with feedforward neural network results can be calculated by the Mean Square Error (MSE) formula as below.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(h_\theta(x^i) - y^i)^2 \quad (7)$$

So that after being trained with a variety of learning rate values, the following results are obtained.

Tabel 2. Error Every LR

No	Number of Iterations	LR	Best Error Value (MSE)
1	1000000	0.1	0.001733699
2	849117	0.2	0.001275407
3	999999	0.3	0.000573247
4	1000000	0.4	0.000526369
5	1000000	0.5	4.52E-06
6	1000000	0.6	0.005735898
7	999999	0.7	0.000115348

No	Number of Iterations	LR	Best Error Value (MSE)
8	780851	0.8	0.02747601
9	1	0.9	0.113782659
10	1	1	0.113782659

Feedforward Neural Network relation with backpropagation results in smallest error value of 4.52E-06 in iteration to one million as in table 2. So the most suitable lr in training Feedforward Neural Network is 0.5. The Weights value generated from lr 0.5 will be used in predicting restaurant density.

2. Information Distribution Application Design

This application modeling uses Unified Modelling Language (UML). UML contained in this application consists of a use case diagram, sequence diagram, and interface design.

In use case diagram, showing that the user can see the splash screen, information about the place, account information, application information, login, change password, create an account, and find a place. On the admin side, admins can do Create Update Read Delete (CURD) to user data, and place data.

The application will be started by opening Splash Screen. At the beginning of the application installed the application will check the internet access, and grant location access. If one of the accesses is not granted the application will stop running. If both accesses are granted the app will check if there is an active account or not. If there is an active account the view will be redirected to the Maps Menu, and otherwise, the view will be redirected to the Login Menu.

In the Login Menu, users can sign in using a previously created application account or a Google account by clicking on the Google logo. In this menu, users can also create an account by clicking on the words "Don't Have Account Yet?", after clicking the user will be redirected to the Registration menu. If the user clicks "Help" the user will be redirected to the Reset Password Menu. When the user clicks login, the user will be redirected to the Maps Menu if the account has been registered in the user database. Or when the user clicks on the Google logo, the app will pop-up the google account option to sign in.

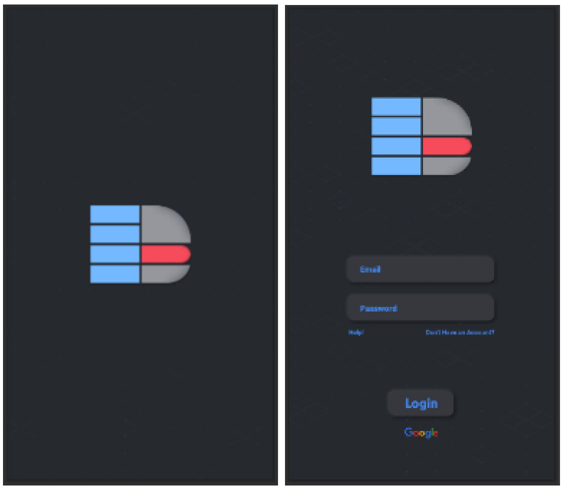
In the Registration Menu, the user can create an account with the email that the user has. When the user registers, the email that the user input will be checked first whether it has previously been registered in the user database.

Reset Password menu is useful to change the password if the user forgets the password used. This menu will check if the email that the user input is registered by clicking on the Google logo or registration on the Registration menu. Accounts created by clicking on the Google logo do not require a password change, users can sign back in the same way. If the account is created by in-app registration, the application will send a password change link to the email to which the password will be changed.

Maps menu will give you a maps view like Google Maps. In this menu, users can search various places other than restaurants, but the data available in the application database is only a few restaurants. By writing the name of the restaurant place, the user will be given a pop-up in the form of information about the restaurant such as the address and density of the restaurant if the restaurant is listed in the application database.

The Profile menu will display the current account data to the user. In this menu, the user can change the account password by clicking "Reset Password". Users can also log out of the application by clicking on the logout, after which the user will be redirected to the login menu again.

User Interface is part of a website, software application, or hardware device that will interact directly with the user. This application is designed with a dark theme to make it more comfortable to see in the long term. This application has six User Interface designs namely Splash Screen design, Login Menu, Registration, Password Reset, Maps, and Profile. The User Interface design has been created in such a way as to facilitate the use of users in using the application. User Interface design uses Adobe Xd application and continued on Android Studio to arrange the look so that it looks like figure 2.



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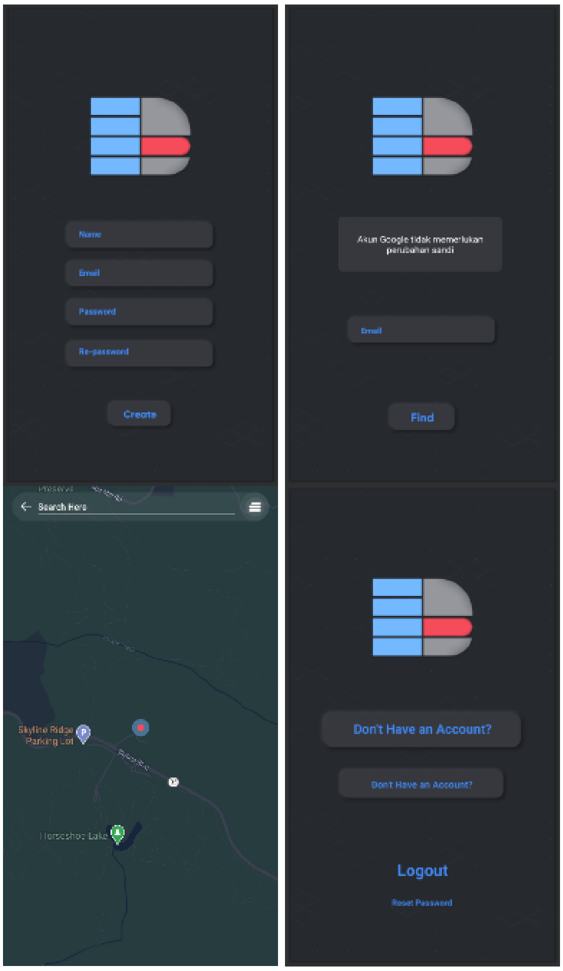

Figure 2. User Interface Application

This app will do two main things, namely getting the user's location from the phone's GPS to be processed in predicting restaurant density (Guo et al., 2019; Hegarty, 2017; Hlavacs & Hummel, 2013; Vatansever & Butun, 2017). Besides, this application will also be used as a means of conveying density information. With this kind of modeling, this application is expected to meet the needs of the community and be easy to use in daily activities.

RESULTS AND DISCUSSION

To test the floor plan system created with a latitude limit of -6.974700 to -6.975000 and longitude 107.629700 to 107.630000. If within kilometers, the simulated area is 33.3 x 33.3 meters or 1108.89 m2. The map that has been prepared next is included the location of the restaurant with a light blue border. The restaurant is located at latitude coordinates -6.974800 to -6.974900 and longitude 107.629900 to 107.629800. After that, the simulation begins by entering random coordinates in the restaurant environment map.

Every five seconds the user coordinates will shift in a random direction with a latitude displacement distance and a longitude of 0.000001 multiplied by a random round number between -10 and 10. This adapts to unpredictable visitor behavior so that random numbers are used. User applications that are inside the light blue line area, will be colored red to indicate they are inside the restaurant, and the user outside will be given black. Every five seconds of the simulation is equal to 5 minutes in the real environment.

Coordinates of restaurant visitors in red will be used as a reference to be the value of system input. First, the system will calculate how many coordinates are dotted red. After that, the system will check how long the red dot is inside the light blue line. If there is a red dot that exits the light blue line, the coordinates will no longer be included in the calculation and will turn into a black dot. Similarly, if a black dot enters a light blue line, it will be a red dot, and be recalculated how long it will last in the light blue line.

Restaurant capacity parameters are entered directly into the database due to their unchanged value. The parameters of the number of visitors are obtained by calculating how many red dots on the simulation map. While the average visitor time parameter is obtained by finding the average time the red dot is inside the light blue line. From the results of a digital simulation run for 10 minutes, data obtained as follows in table 3.

Tabel 3. Inputs and System Results Based on Simulation Data

No	C	P	AT	Den	Des	M%
1	20	11	5	0.33	S	0
2	20	12	9.17	0.45	S	0
3	20	12	13.75	0.51	P	100
4	20	13	17.69	0.58	P	100
5	20	12	22.92	0.59	P	100
6	20	17	19.71	0.76	SP	100
7	20	12	26.67	0.62	P	100
8	20	9	34.44	0.62	P	100
9	20	9	28.89	0.56	P	0
10	20	10	30.5	0.61	P	100
11	20	11	32.27	0.64	P	100
12	20	12	34.17	0.65	P	100
13	20	10	42	0.67	P	100
14	20	10	40.5	0.67	P	100
15	20	12	38.33	0.67	P	100
16	20	10	47.5	0.68	P	100
17	20	8	56.88	0.67	P	100
18	20	11	45.91	0.68	P	100
19	20	11	50	0.68	P	100
20	20	12	47.5	0.67	P	100
21	20	13	47.69	0.67	P	100
22	20	12	55	0.66	P	100
23	20	11	61.82	0.66	P	100
24	20	14	50	0.66	P	100
25	20	12	60	0.65	P	100
26	20	12	53.75	0.67	P	100

No	C	P	AT	Den	Des	M%
27	20	12	55.83	0.66	P	100
28	20	12	57.92	0.66	P	100
29	20	12	62.5	0.65	P	100
30	20	11	71.82	0.64	P	100
31	20	12	68.75	0.64	P	100
32	20	12	60.42	0.65	P	100
33	20	10	59	0.67	P	100
34	20	9	62.78	0.67	P	100
35	20	11	54.55	0.67	P	100
36	20	11	58.64	0.67	P	100
37	20	11	53.64	0.67	P	100
38	20	12	53.33	0.67	P	100
39	20	12	56.67	0.66	P	100
40	20	7	62.86	0.66	P	100
41	20	10	49	0.68	P	100
42	20	11	48.18	0.68	P	100
43	20	10	57	0.68	P	100
44	20	11	55.45	0.67	P	100
45	20	13	50.38	0.66	P	100
46	20	12	57.92	0.66	P	100
47	20	10	72.5	0.65	P	100
48	20	10	77	0.65	P	100
49	20	11	74.55	0.64	P	100
50	20	10	86.5	0.66	P	100
51	20	13	65	0.64	P	100
52	20	9	91.67	0.69	P	0
53	20	10	87.5	0.66	P	100
54	20	12	77.92	0.63	P	100
55	20	13	76.92	0.63	P	100
56	20	14	76.43	0.63	P	100
57	20	14	81.07	0.64	P	100
58	20	13	91.15	0.67	P	0
59	20	13	89.23	0.66	P	100
60	20	14	87.86	0.66	P	100
61	20	12	103.75	0.76	SP	100
62	20	12	108.75	0.8	SP	100
63	20	12	102.08	0.74	P	0
64	20	13	98.85	0.72	P	0
65	20	11	109.55	0.8	SP	100
66	20	12	102.5	0.75	P	0
67	20	11	115.91	0.85	SP	100
68	20	14	95.71	0.7	P	0
69	20	14	100	0.74	P	0
70	20	14	105	0.77	SP	100
71	20	15	79.67	0.65	P	100
72	20	13	95	0.69	P	0
73	20	12	107.5	0.79	SP	100
74	20	14	97.14	0.71	P	0
75	20	14	102.14	0.75	P	0
76	20	13	95.77	0.7	P	0
77	20	11	115.45	0.85	SP	100
78	20	13	102.69	0.75	P	0
79	20	12	115.83	0.85	SP	100
80	20	13	111.92	0.82	SP	100
81	20	14	108.93	0.81	SP	100
82	20	14	112.86	0.83	SP	100
83	20	13	120	0.88	SP	100
84	20	13	120	0.88	SP	100
85	20	13	120	0.88	SP	100
86	20	14	120	0.88	SP	100
87	20	14	120	0.88	SP	100
88	20	13	120	0.88	SP	100
89	20	13	120	0.88	SP	100
90	20	12	120	0.88	SP	100
91	20	14	120	0.88	SP	100
92	20	15	120	0.88	SP	100
93	20	13	120	0.88	SP	100
94	20	13	120	0.88	SP	100
95	20	13	120	0.88	SP	100
96	20	15	120	0.88	SP	100
97	20	14	120	0.88	SP	100
98	20	14	120	0.88	SP	100
99	20	14	120	0.88	SP	100
100	20	14	120	0.88	SP	100
101	20	13	120	0.88	SP	100
102	20	13	120	0.88	SP	100
103	20	13	120	0.88	SP	100
104	20	12	120	0.88	SP	100
105	20	10	120	0.88	SP	100
106	20	12	120	0.88	SP	100
107	20	12	120	0.88	SP	100
108	20	13	120	0.88	SP	100
109	20	10	120	0.88	SP	100
110	20	14	120	0.88	SP	100
111	20	16	120	0.87	SP	100
112	20	15	120	0.88	SP	100
113	20	16	120	0.87	SP	100
114	20	15	120	0.88	SP	100
115	20	15	120	0.88	SP	100
116	20	14	120	0.88	SP	100
117	20	14	120	0.88	SP	100
118	20	13	120	0.88	SP	100
119	20	13	120	0.88	SP	100
120	20	15	120	0.88	SP	100
Average Matches						87.5

From table 3 the density value can be based only on simulations that are in such a way as to be identical to the original environment. The match rate between the system output and the respondent classification reaches 87.5%, which means that the system is possible to be developed further. For the prediction test, the journal entitled Restaurant Revenue Management (Studi Kasus Restoran Xx Ngaliyan Semarang) obtained data such as the table below in table 4 (Fuadillah & Suliantoro, 2016).

Tabel 4. Percentage Data of Filled Capacity

Ho	Mo	Tu	We	Th	Fr	Sa	Su
10	3	3	3	3	3	2	1
11	17	16	17	16	16	10	6
12	43	42	43	43	28	17	10
13	59	54	55	57	43	18	12
14	39	36	36	35	57	28	18
15	24	24	23	21	31	24	18
16	15	15	15	14	14	13	8
17	16	14	14	15	15	10	3
18	17	13	16	14	16	18	3
19	24	23	25	23	23	32	20
20	9	9	9	10	10	14	16
21	1	1	1	1	1	3	1
22	0	0	0	0	0	0	0

The journal also obtained data on the average length of visitors in the restaurant is 54 minutes 36 seconds. So that the data obtained

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restaurant density based on the classification determined by respondents as table 5.

Table 5. Restaurant Density Data According to Respondent Classification

Ho	Mo	Tu	We	Th	Fr	Sa	Su
10	M	M	M	M	M	M	M
11	M	M	M	M	M	M	M
12	F	F	F	F	F	M	M
13	F	F	F	F	F	M	M
14	F	F	F	F	F	F	M
15	M	M	M	M	F	M	M
16	M	M	M	M	M	M	M
17	M	M	M	M	M	M	M
18	M	M	M	M	M	M	M
19	M	M	M	M	M	F	M
20	M	M	M	M	M	M	M
21	M	M	M	M	M	M	M
22	E	E	E	E	E	E	E

The data is used as system input to predict. The predicted result of the system from the data input is as in table 6.

Tabel 6. System Output Based on Original Data

Ho	Mo	Tu	We	Th	Fr	Sa	Su
10	M	M	M	M	M	M	M
11	M	M	M	M	M	M	M
12	F	F	F	F	M	M	M
13	F	F	F	F	F	M	M
14	F	F	F	F	F	M	M
15	M	M	M	M	F	M	M
16	M	M	M	M	M	M	M
17	M	M	M	M	M	M	M
18	M	M	M	M	M	M	M
19	M	M	M	M	M	F	M
20	M	M	M	M	M	M	M
21	M	M	M	M	M	M	M
22	E	E	E	E	E	E	E

From input data as many as 91 conditions, the system predicts 89 conditions correctly or the suitability of the system with the original data reaches 97.8. Next, to test the application, beta testing is used to see application performance. Apps are shared through questionnaires and users review app performance, and views. the results of beta testing areas table 7.

Table 7. List of Questions

No	Question
1	Is the Restaurant Density Prediction app convenient to use?
2	Can the information displayed in the Restaurant Density Prediction app be captured easily and clearly?
3	Is the help feature in the Restaurant Density Prediction app helpful?
4	Does the Restaurant Density Prediction app fit the user's needs?
5	Is the display on the Restaurant Density Prediction app comfortable to look at?
6	Are menu views, features, and symbols in the Restaurant Density Prediction app easy to spot?
7	Is the font size displayed in the Restaurant Density Prediction app easy to read?
8	Is the "create account" and "login" process easy to use?

from the list of questions above, the respondents' responses are as follows.

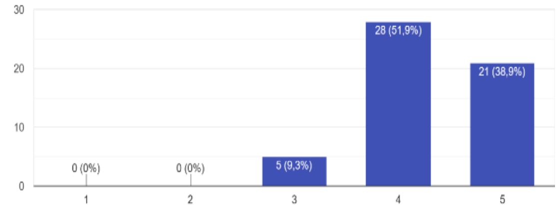

Figure 3. Question 1

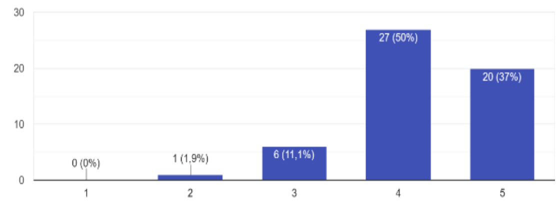

Figure 4. Question 2

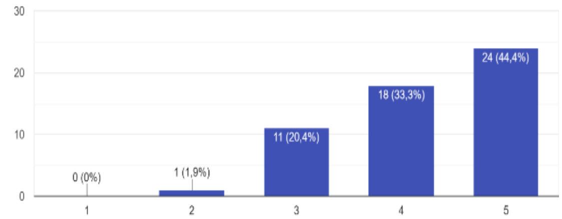

Figure 5. Question 3

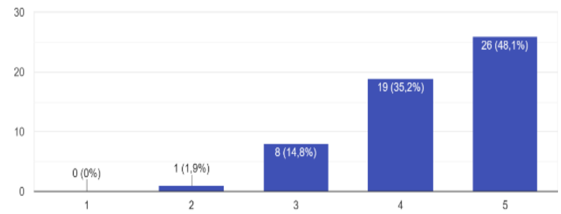

Figure 6. Question 4

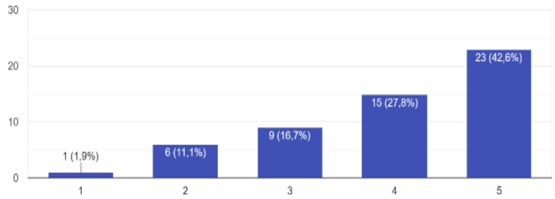

Figure 7. Question 5

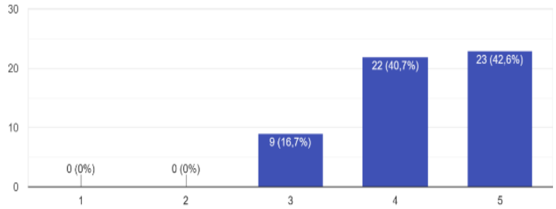

Figure 8. Question 6

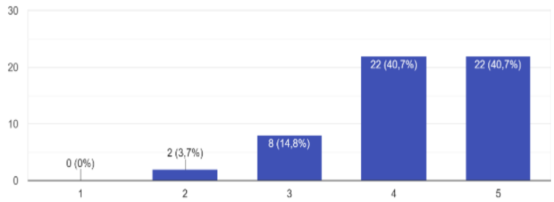

Figure 9. Question 7

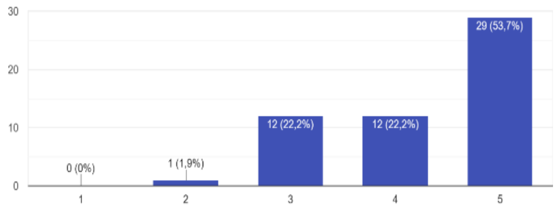

Figure 10. Question 8

From each of these questions the result from the respondent's is in figure 3 and so on until figure 10, the higher the value the better the respondent's assessment of this application. But some respondents rated low on question number five about the appearance of the interface. This may be based on respondents who are not very comfortable using dark mode. Some respondents also rated poorly on the size and color of letters that were a little difficult to read on question number seven. But overall, the app is welcomed by the community. From the results above, this research may still be very early and should be developed further, such as making applications that can be more optimization, and the use of other parameters in the contradiction. More datasets can make this system better. The lack of accurate mapping technology makes the accuracy of density determinants decrease. This system will be excellent when combined with a 3D positioning system. Unfortunately, 3 Dimension positioning system is difficult to implement with various factors.

CONCLUSIONS AND SUGGESTIONS

Conclusions

Feedforward Neural Network is quite good for predicting restaurant density with FSF method, by using adam optimizer and relu activation function, Feedforward Neural Network can match output with existing data with an MSE value of 7.585e-06 and a test MSE value of 0. 006923. The mobile application of restaurant density information can be built with Java programming language as well as some additional APIs such as Place API, Firebase API, etc. The design of the adobe Xd interface is very easy to elaborate on in setting up the interface to be used in the application. this application is welcomed in the community, proven by good assessment obtained from respondents' reviews. based on the above, the purpose of the research to provide information on restaurant density has been achieved by the application of restaurant density information and a restaurant density prediction system.

Suggestions

Using other neural network architectures to predict restaurant density such as RNN, or can use other optimization functions and other activation functions such as sigmoid. Restaurant density information applications can be created also in other operating systems such as iOS. Added normal mode to better cover users who are not very comfortable with dark mode. Add color and write-based settings to the app.

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