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Application of *fuzzy genetic system* to predict the number of outpatient visits

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ABSTRACT

Improving the management and use of resources in outpatient care is a challenge faced by health facilities in today's digital era. The inability to accurately predict patient flow can result in inadequacies in staff scheduling and effective space management. Therefore, this study aims to develop a predictive model of outpatient visits using the fuzzy system genetic method. The research methods used include the design of a combination of experimental methods, quantitative analysis, and model validation. Outpatient visit data is taken from a hospital and processed using the Fuzzy Genetics System which optimizes fuzzy rules with genetic algorithms. The results of the model implementation show accurate and adaptive predictions to variations and uncertainties in patient visiting patterns. Based on the results of the study, it can be concluded that the use of fuzzy system genetic methods in predicting outpatient visits can improve the operational efficiency of health facilities. The developed prediction model is able to provide predictions that are more accurate, adaptive, and responsive to the real needs of health facilities. With the adoption of this method, health facilities can optimize management and resources in outpatient health services. This research contributes significantly to the development of predictive models that are more efficient and applicable in the dynamic context of healthcare.

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1. INTRODUCTION

In today's digital era, the health world continues to face challenges in optimizing management and resources, especially in outpatient care (Alidina et al., 2021) (Luo et al., 2020). As populations grow and access to healthcare increases, medical facilities often become overloaded due to unpredictable patient visits (Bhandari et al., 2020). This inability to predict patient flow can lead to inadequacies in staff scheduling, availability of medical equipment, and effective space management, potentially degrading the quality of healthcare (Yu et al., 2020).

This issue is important because it directly affects the operational efficiency of health facilities as well as the quality of services provided to patients (Mousa & Othman, 2020) (Halawa et al., 2020). Accurately predicting the number of patient visits not only optimizes resource usage but also increases patient satisfaction and reduces wait times (Iwendi et al., 2020) (Deng et al., 2023).

The study was conducted to address deficiencies in existing prediction methods, which often do not account for variability and blurring in patient visiting patterns (Weaver et al., 2020).

Therefore, this study propose the use of fuzzy system genetic methods as an innovative approach to overcome this problem (Garud et al., 2021).

Previous research exploring the use of a hybrid approach between genetic algorithms and fuzzy logic to predict outpatient flow in hospitals has shown that this method produces accurate and flexible predictions, able to overcome variability and blurring in patient visit patterns (Singh et al., 2019). Research focused on developing fuzzy genetic algorithms to predict outpatient visits in primary healthcare centers managed to provide accurate predictions by considering diverse factors affecting patient flow (Safdar et al., 2021). The study proposing an outpatient arrival prediction model in polyclinic departments using a combination of fuzzy logic and genetic algorithms successfully overcame variation and uncertainty in patient visit patterns, resulting in accurate and adaptive predictions (Munir et al., 2019). Research that applied fuzzy genetic algorithms to predict outpatient visits in hospitals succeeded in producing accurate predictions by considering variations and uncertainties in patient visit patterns (Wynants et al., 2020). Research integrating fuzzy genetic algorithm approaches in outpatient appointment scheduling and patient flow prediction improved operational efficiency in healthcare by considering blurriness and variation in patient visitation patterns (Wang et al., 2022).

Some researchers are focusing on using a hybrid approach between genetic algorithms and fuzzy logic to predict outpatient flow in hospitals, which has been shown to produce accurate and flexible predictions, and overcome variability and blurring in patient visiting patterns. However, there is limited research relating to the development of fuzzy genetic algorithms to predict outpatient visits in primary health care centers, polyclinic departments, as well as advanced hospitals. Therefore, this study intends to fill the gap in the literature by developing an outpatient arrival prediction model that uses a combination of fuzzy logic and genetic algorithms, as well as integrating fuzzy genetic algorithm approaches in outpatient appointment scheduling and patient flow prediction. The purpose of this study is to produce more accurate, adaptive, and efficient predictions in optimizing outpatient health service management and resources.

The approach proposed in this research offers an innovative solution by integrating fuzzy logic and genetic algorithms to overcome the limitations of previous prediction methods that often fail to account for variability and uncertainty in patient visiting patterns. The combination of these two techniques enables the development of an adaptive and responsive prediction model that can handle the inherent complexities and uncertainties in healthcare data. Specifically, the fuzzy system component provides a robust framework for managing imprecise or vague information, while the genetic algorithm component optimizes the fuzzy rules, leading to more accurate and reliable predictions. Compared to previous studies, this approach offers a superior solution in addressing variations and uncertainties in patient visit patterns. This research focuses on developing an outpatient arrival prediction model for a specific hospital, RSUD dr. Soeselo Slawi, which encompasses 18 polyclinic departments, thereby providing a practical and effective solution for optimizing resource management and enhancing operational efficiency in outpatient services.

2. RESEARCH METHOD

Research Design

This study used a combination design of experimental methods, quantitative analysis, and model validation. The experiment was conducted by applying the Fuzzy Genetics System to outpatient visit data (Yang et al., 2020) (Król & Sierpiński, 2021). Quantitative analysis is carried out to process experimental data, and model validation is carried out to evaluate the effectiveness of the developed model (Wong et al., 2021).

Figure 1. Research flow

Based on Figure 1 Showing the flow of research starting from data collection, this research data is outpatient visit data obtained online on the website. Data on outpatient visits at Soeselo Slawi Hospital as many as 18 clinics. Each poly had the number of monthly outpatient visits in

2021. Then the implementation of the Fuzzy Genetics System is optimizing the Fuzzy rules with the Genetic Algorithm. Furthermore, evaluate the results of the implementation of the Fuzzy Genetic System using the performance of genetic algorithms, evaluate the performance of genetic algorithms in optimizing fuzzy rules.

Data Gathering

Table 1. Outpatient data

NO	CLINIC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUGST	SEP	OCT	NOV	DEC	SUM
1	Child	322	308	320	378	366	313	248	341	379	418	488	614	4495
2	Orthopaedic Surgery	206	213	254	255	201	205	152	218	217	232	304	413	2870
3	General Surgery	425	328	491	518	440	542	316	323	483	423	562	862	5713
4	Urological Surgery	317	292	375	410	392	242	301	361	366	380	405	493	4334
5	Tooth	38	96	134	114	115	82	44	69	147	139	166	233	1377
6	Dental Oral Surgery	122	136	159	156	112	146	107	148	158	151	168	203	1766
7	Heart	1306	1202	1345	1255	1099	1165	1086	1220	1229	1203	1274	1527	14911
8	Obstetrics & Pregnancy	228	202	245	300	255	240	127	153	230	296	267	350	2893
9	Spirit/Beast	597	600	693	657	632	644	614	695	727	641	709	819	8028
10	Skin & Genitals	126	110	131	114	106	112	73	95	156	134	147	268	1572
11	Eye	420	394	485	523	408	446	325	416	507	541	689	898	6052
12	Lungs	313	266	315	294	345	302	245	256	295	295	401	558	3885
13	Internal Medicine	1518	1555	1809	1822	1670	1769	1498	1436	1737	1769	1876	2096	20555
14	Psychology	12	9	11	19	9	31	11	23	31	19	23	32	230
15	Nerve	1124	1066	1208	1206	1008	1201	1016	1097	1128	1217	1161	1367	13799
16	TB. MDR	2	8	22	20	21	2	5	11	12	9	10	157	279
17	Otolaryngologist	223	225	278	287	239	297	166	201	270	296	296	410	3188
18	General	63	79	204	92	74	80	175	99	102	36	136	624	1764
Sum		7362	7089	8479	8420	7492	7819	6509	7162	8174	8199	9082	11924	97711

Source : RSUD dr. Soeselo - Data Kunjungan Rawat Jalan Tahun 2021 - Kumpulan data - Data Terbuka - Kabupaten Tegal (tegalkab.go.id).

Based on Table 1 Shows Outpatient visit data taken from the official website of Open Data of Tegal Regency, including information such as month of visit, type of clinic, and number of patients. The data contains 18 clinics at RSUD Soeselo Slawi, each clinic has the number of outpatient visits every month in the year. The number of outpatient visits at RSUD Soeselo Slawi was 97,711 patients, this number was the total visits from 18 clinics at RSUD Soeselo Slawi.

Pre-processing Data

The data obtained will go through a data pre-processing process that includes cleaning the data by removing columns that are not needed for the calculation process. The column that is deleted in the data that has been obtained is to delete the number column.

Algorithm Implementation

Genetic algorithms and Fuzzy Systems are implemented using Python programming language. Genetic algorithms are used for solution search optimization, while Fuzzy Systems are used to handle uncertainty and impreciability in data (Decerle et al., 2019).

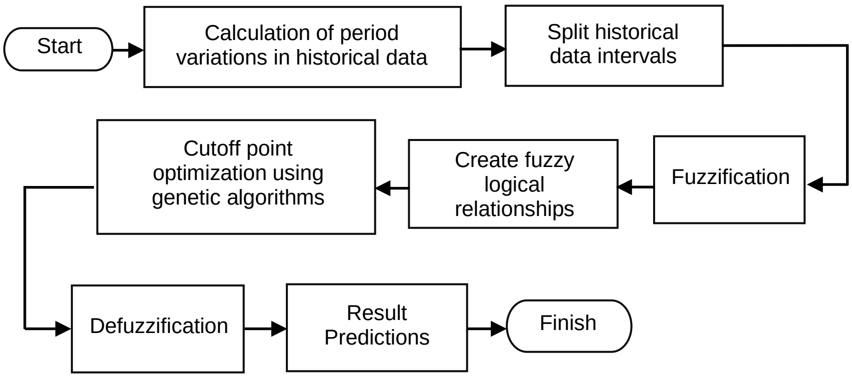

Figure 2. Flowchat implementation of fuzzy system genetic algorithm

Based on Figure 2 shown flowchart implementation of the Fuzzy System Genetics method starting from the calculation of period variations in historical data, variations are used in determining the amount of difference in data to be used. The next stage divides the interval of historical data, the length of the interval is very influential in the formation of rules in fuzzy which will give a difference in the results of prediction calculations. Therefore the formation of rules in fuzzy must be precise and the length of the interval should not be too long and should not be too short. Fuzzification in Genetics Fuzzy System is important in converting numerical input variables into linguistic values or fuzzy sets, enabling the handling of uncertainty and complexity of outpatient data. Fuzzification is a key step in creating predictive models that are accurate and responsive to the unique characteristics of each patient. The Fuzzification formula can be written in equation (1)

$$\mu A\ (x) = f(x - a) \tag{1}$$

Where $\mu A\ (x)$ is the degree of membership value x in fuzzy sets A, f is a fuzzy function used to map values x into fuzzy sets A, a is the central value of the fuzzy set A (Talpur et al., 2022).

The next stage creates fuzzy logical relationships, determining fuzzy logic relationships obtained from fuzzy values at the Fuzzification stage. Furthermore, cutoff point optimization uses a genetic algorithm, the intersection point at each interval is then optimized using a genetic algorithm, when optimization there is a process of calculating fitness values to find the best fitness that serves to minimize error values when optimization. The formula for calculating fitness values is written in equation (2)

$$I = \sqrt{\frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n}} \tag{2}$$

Where n is the amount of data, $\hat{y}_t$ is the result obtained from the fuzzy process, y_t is the result you already have as input, t is the order of the enter variable (Hamdia et al., 2021). Then Defuzzification, the prediction of values at the previous stage. Application of defuzzification using formulas in equation (3)

$$Y = \sum w_i * f_i\,(x_i) \tag{3}$$

Where Y is the predicted value of the number of outpatient visits, w_i is the weight of the fuzzy rule, f_i is a fuzzy rule membership function , x_i is the input value. After defuzzification, it will display the prediction results (Verma et al., 2020).

Model Evaluation

Model evaluation is performed using the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics to assess the accuracy of model predictions against actual data (Mamun et al., 2020). The formula for Mean Absolute Percentage Error (MAPE) is written in equation (4)

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{n} * 100 \tag{4}$$

Where n is the amount of data, i is the order of data on the database, y_i is actual and $\hat{y}_i$ is the predicted value (Khan & Byun, 2020).
The Root Mean Square Error (RMSE) formula can be written in equation (5)

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{(\,y^i - \acute{y})^2}{n}} \tag{5}$$

Where n is the number of samples in the data, y^i is actual and $\acute{y}^i$ is the predicted value.
The formula Mean Absolute Error (MAE) can be written in equation (6)

$$\text{MAE} = \left(\frac{1}{n}\right) * \sum |i = 1|{}^\wedge n|y^i - \acute{y}^i| \tag{6}$$

Where n is the number of samples in the data, y^i is actual and $\acute{y}^i$ is the predicted value (Tabbussum & Dar, 2021).

3. RESULTS AND DISCUSSIONS

The pre-processing phase of research data, cleaning is important to streamline the data set for subsequent analysis. The action taken is the removal of the column 'NO', which contains the numerical identifier for the clinic. This column is considered unimportant for our predictive modeling purposes, as it contributes no predictive value and serves only as an index. Focusing on clinic names and monthly visit data respectively, can ensure that the analysis is relevant to the predicted patterns. This reduces data complexity, enabling more efficient handling and processing in later stages of our methodology.

Table 2. Data after normalization

CLINIC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUGST	SEP	OCT	NOV	DEC	SUM
Child	322	308	320	378	366	313	248	341	379	418	488	614	4495
Orthopaedic Surgery	206	213	254	255	201	205	152	218	217	232	304	413	2870
General Surgery	425	328	491	518	440	542	316	323	483	423	562	862	5713

CLINIC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUGST	SEP	OCT	NOV	DEC	SUM
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Psychology	12	9	11	19	9	31	11	23	31	19	23	32	230
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Otolaryngologist	223	225	278	287	239	297	166	201	270	296	296	410	3188
General	63	79	204	92	74	80	175	99	102	36	136	624	1764
Sum	7362	7089	8479	8420	7492	7819	6509	7162	8174	8199	9082	11924	97711

Table 2 shows data after normalization by deleting columns NO, The cleaned dataset stores monthly visits data for each clinic from January to December, in addition to total annual visits, which is critical for understanding annual trends and preparing data for fuzzy logic-based prediction systems. This simplified data set forms the basis for accurate and effective modeling, ensuring that all included variables are relevant and contribute meaningfully to prediction results.

The implementation phase of the algorithm, an advanced predictive model using fuzzy logic is used to estimate future outpatient visits in various clinical departments. This algorithm takes historical data as a reference to get prediction results. This approach was chosen for its resilience in addressing the uncertainty and variability inherent in healthcare data. The model processes normalized data, along with calculated measures of variation that measure fluctuations in patient visits throughout the year. Each clinic's data is categorized into high or medium variation categories based on these measures, which guide fuzzy systems in handling data differently depending on the degree of variability.

Table 3. Results of fuzzy system genetic implementation

Variation	Category	Predicted
1146	High	524
732	High	405
1459	High	524
1103	High	522
353	High	322
449	High	350
3792	High	524
737	High	407
2041	Medium	524
402	High	345
1545	High	524
991	High	514
5228	High	524
59	High	84

Based on Table 3 What is presented, it can be seen that there is a predicted value for the "High" category variation and one line for the "Medium" category. For the "High" category, the predicted value varies from 84 to 524. The value 524 appears most often, seen on six different rows, including the variation with the highest value, which is 3792. The lowest score for this category was 84 on the 59 variation. Other variations show values such as 405, 407, 350, 514, and 345. Meanwhile, there is a row for the "Medium" category with a variation of 2041 and the same predicted value as the highest value in the "High" category, which is 524. This may indicate that the value 524 may represent a certain threshold or level in the measurement. The results obtained are then evaluated Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

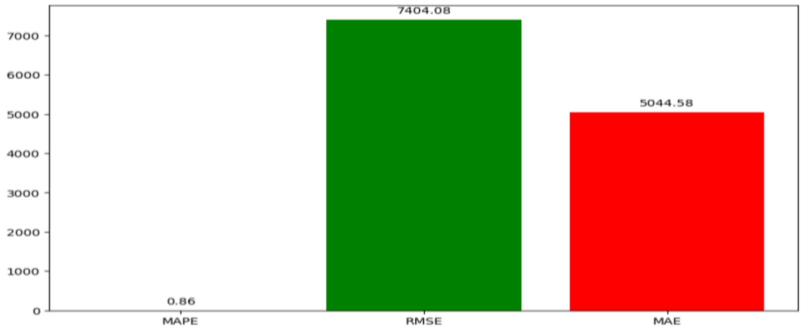

Figure 3. Model evaluation

Based It can be seen that the obtained MAPE value is 0.86%, which indicates that the average absolute error percentage of the model's prediction of the true value is very small, so the model has high accuracy. An RMSE value of 7404.08 indicates that the model has a considerable mean squared deviation, which indicates the presence of some predictions that are far from the actual value. Meanwhile, an MAE value of 5044.58 indicates that the average absolute error of the prediction is 5044.58. As a result of this evaluation, it can be concluded that although the model has a high level of accuracy (indicated by the low MAPE value), there are some predictions that are quite far from the actual value, which is reflected in the high RMSE value. A lower MAE value compared to the RMSE indicates that despite outliers causing major deviations, The overall average absolute error of the prediction is still within acceptable limits.

Results of this research makes a significant contribution by developing an accurate and robust outpatient visit prediction model using the fuzzy genetic system method. Compared to previous studies, this research presents quantitative performance metrics such as MAPE (0.86%), RMSE (7404.08), and MAE (5044.58). The low MAPE value indicates high accuracy, surpassing some previous studies, while the relatively high RMSE value indicates a need for improvement in handling outliers. Nevertheless, the maintained MAE value demonstrates the potential for practical application in healthcare facilities. This research paves the way for further studies in enhancing the model's adaptability to dynamic healthcare environments.

4. CONCLUSION

This research makes significant contributions both theoretically and practically. Theoretically, it enhances literature by developing an efficient predictive model for healthcare services using fuzzy systems and genetic algorithms, providing accurate, adaptive predictions of patient visit patterns. Practically, the model aids practitioners in efficient resource planning through better staff scheduling, equipment availability, and space utilization, improving operational efficiency and service quality. It also serves as a strategic tool for stakeholders, enabling accurate forecasting of resource needs, budget allocation, and facility planning based on patient visit trends, thus supporting long-term planning and efficient resource utilization in healthcare. Future studies should explore the utilization of more diverse datasets spanning longer time periods to enhance the reliability of predictions. Additionally, it is advisable to consider predictive models capable of accounting for outliers more effectively, as this would further improve accuracy and robustness of the forecasting models

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