Prediction of Patient Arrivals per Room at NTB Provincial Hospital Using the Auto SARIMA Model

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Abstrak

Rumah Sakit Umum Daerah (RSUD) Provinsi NTB merupakan rumah sakit rujukan utama di Nusa Tenggara Barat yang menghadapi tantangan dalam mengelola fluktuasi jumlah pasien. Lonjakan pasien dapat menyebabkan kekurangan sumber daya medis, sementara penurunan jumlah pasien berisiko menyebabkan pemborosan sumber daya. Oleh karena itu, diperlukan sistem prediksi yang mampu memperkirakan jumlah kedatangan pasien secara akurat guna mendukung manajemen rumah sakit. Penelitian ini bertujuan untuk mengembangkan model prediksi jumlah pasien menggunakan Auto SARIMA (Seasonal AutoRegressive Integrated Moving Average). Data yang digunakan mencakup informasi tanggal masuk, tanggal keluar, asal masuk (IGD atau poli), serta jenis pembayaran pasien (BPJS, PBI, NPBI, dan umum). Selain itu, model ini mempertimbangkan faktor eksternal seperti hari libur, kondisi cuaca, dan kejadian khusus yang berpotensi memengaruhi jumlah pasien.Tahapan penelitian meliputi pengumpulan dan pra-pemrosesan data, pemodelan menggunakan Auto SARIMA, serta evaluasi hasil prediksi dengan Mean Absolute Error (MAE) dan Root Mean Square Error (RMSE). Hasil evaluasi model dengan menggunakan metrik statistik menunjukkan performa yang cukup baik, dengan nilai Mean Absolute Error (MAE) sebesar 3,61 dan Root Mean Square Error (RMSE) sebesar 5,33. Nilai ini mengindikasikan bahwa tingkat kesalahan prediksi relatif kecil, sehingga model Auto SARIMA dapat diandalkan dalam memperkirakan jumlah pasien per kamar. Prediksi Auto SARIMA memberikan manfaat praktis bagi rumah sakit. Pola musiman kedatangan pasien yang teridentifikasi dapat digunakan untuk mengoptimalkan pengelolaan kamar rawat inap, perencanaan sumber daya medis, serta penjadwalan pelayanan kesehatan secara lebih efisien.

Kata kunci: *RSUD Provinsi NTB, prediksi jumlah pasien, Auto SARIMA, Manajemen rumah sakit*

Abstract

The Regional General Hospital (RSUD) of West Nusa Tenggara Province serves as the primary referral hospital in the region, facing challenges in managing fluctuations in patient numbers. A surge in patients can lead to shortages of medical resources, while a decline in patient numbers may result in resource wastage. Therefore, a prediction system capable of accurately forecasting patient arrivals is necessary to support hospital management. This study aims to develop a patient arrival prediction model using Auto SARIMA (Seasonal AutoRegressive Integrated Moving Average). The data used includes information on admission and discharge dates, the source of admission (ER or clinic), and the type of patient payment (BPJS, PBI, NPBI, and general). Additionally, the model considers external factors such as public holidays, weather conditions, and special events that may influence patient numbers. The research stages include data collection and preprocessing, modeling using Auto SARIMA, and evaluating prediction results using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The evaluation results indicate that the Auto SARIMA model effectively captures the seasonal patterns of patient arrivals, achieving an MAE of 3.61 and an RMSE of 5.33. A questionnaire-based assessment showed that the implementation of the Auto SARIMA model for predicting patient arrivals at the NTB Provincial Hospital received an approval rating of 84.7%, categorized as Strongly Agree. These results demonstrate that the prediction model can serve as a reliable tool for managing inpatient rooms, resource allocation, and medical staff scheduling more efficiently

Keywords: *NTB Provincial Hospital, Patient arrival prediction,Auto SARIMA,Hospital management,Operational efficiency.*

1. INTRODUCTION

The Provincial Regional General Hospital (RSUD) of West Nusa Tenggara (NTB) serves as one of the main pillars of the province's healthcare system. As a provincial referral hospital, RSUD NTB is responsible for providing medical services to the community, including emergency care and long-term treatment. In addition to serving patients from within the province, the hospital also receives referrals from surrounding areas, making it a crucial healthcare center in the region [1]. A hospital is an organization that provides healthcare services through organized medical professionals and permanent medical facilities. According to [2], hospitals offer various healthcare services, including medical treatment, continuous nursing care, and the diagnosis and treatment of diseases for patients. Hospitals play a vital role in the healthcare system, serving as the primary location for the community to access affordable and quality healthcare services.

Based on the Decree of the Minister of Health of the Republic of Indonesia, hospitals are not only responsible for providing healthcare services but also play a crucial role in the education of healthcare professionals and medical research. Hospitals serve as practical training grounds for medical students, nurses, and other healthcare professionals, enhancing their skills through hands-on experience. Additionally, hospitals act as research centers that contribute to the advancement of medical knowledge and healthcare innovations. According to [3],, hospitals function as a subsystem within the healthcare system, offering two primary types of services: healthcare services and administrative services. Healthcare services encompass medical treatment, medical rehabilitation, and patient care provided through emergency units, outpatient units, and inpatient units. Emergency units handle critical patients requiring immediate medical attention, while outpatient units cater to patients needing medical consultations and treatments without hospitalization. Inpatient units, on the other hand, accommodate patients requiring further care over a specific period.

Apart from medical services, hospitals also offer administrative or non-medical services managed by administrative personnel. As stated in [4], administrative personnel play a significant role in managing non-medical aspects, including human resources, finances, and hospital operations. They ensure the smooth operation of the hospital's management system and maintain compliance with established standards and policies determined by the Hospital Board of Trustees. Administrative services also involve managing patient data, hospital information systems, and other supporting services such as logistics and hospital sanitation. According to the Decree of the Minister of Health of the Republic of Indonesia No. 983/Menkes/17/1992, general hospitals are classified based on the level of healthcare services they provide, including Class A, Class B (both educational and non-educational), Class C, and Class D hospitals [5]. Class A hospitals have the most comprehensive facilities and medical specialists, offering extensive sub-specialist services compared to other classes. Class B hospitals provide specialist and sub-specialist services, although not as extensive as Class A hospitals. Class C hospitals offer limited specialist services, while Class D hospitals primarily provide basic healthcare services with fewer specialist options.

As hospitals continue to develop, they face various challenges, such as increasing patient numbers, the demand for advanced healthcare technologies, and the need to provide fast and high-quality services. Therefore, innovations in hospital service systems, such as the implementation of electronic medical records and digital hospital management systems, play a crucial role in enhancing healthcare service effectiveness and efficiency. Through continuous innovation and effective management, hospitals can maintain their role as the frontline institutions in ensuring and improving public health. However, in fulfilling its role, RSUD NTB faces significant challenges in managing the unpredictable influx of patients. Observations indicate that fluctuations in patient numbers can be influenced by various factors, including seasonal shifts, weather conditions, and specific epidemiological situations. This uncertainty complicates hospital resource planning, such as the availability of patient rooms, medical staff, and medical equipment. Unexpected surges in patient numbers can lead to resource shortages, compromising the quality of care. Conversely, lower-than-expected patient numbers may result in inefficient resource utilization and wastage [6].

To address these challenges, a more effective management strategy is required to predict patient arrivals. One promising solution is the application of an Auto SARIMA (Seasonal AutoRegressive Integrated Moving Average) model [7]. This model enables hospitals to identify patient arrival patterns based on historical data, seasonal factors, and long-term trends. By implementing this model, hospital management can allocate resources more efficiently, ensuring the availability of medical staff, patient rooms, and equipment based on actual needs. The primary objective of applying the Auto SARIMA prediction model is to enhance the operational efficiency of RSUD NTB by optimizing resource management. With more accurate predictions, the hospital can minimize the risk of medical staff shortages during patient surges and prevent resource wastage during periods of low patient numbers. Additionally, this prediction system is expected to improve the quality of healthcare services by ensuring that every patient receives timely and appropriate care without unnecessary delays or disruptions.

2. RESEARCH METHOD

This study aims to predict patient arrivals per room at the NTB Provincial Hospital using the Auto SARIMA model. This study was conducted by utilizing historical patient arrival data that was already available, through systematic stages to build an accurate prediction model.

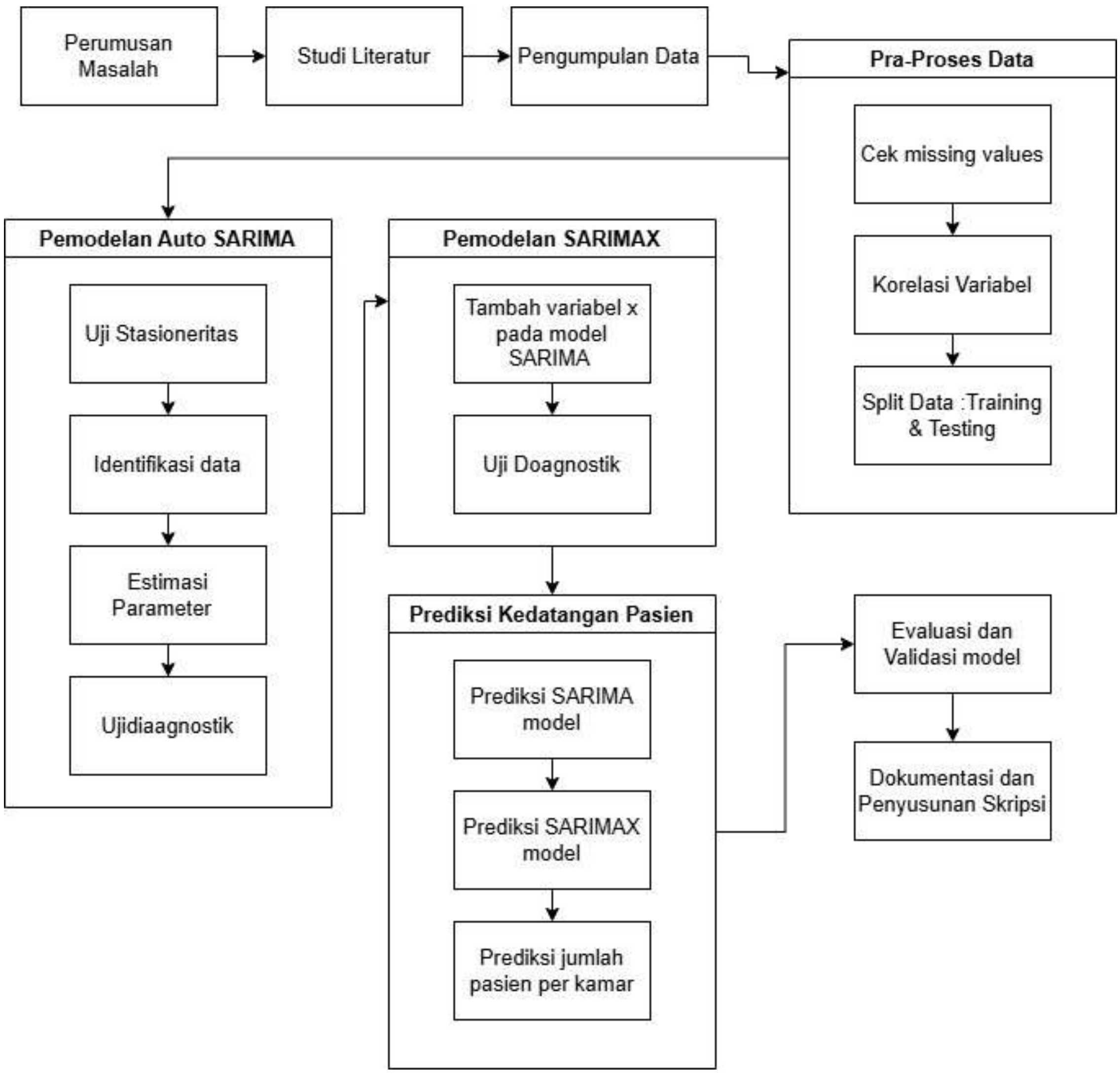

Figure 1 Research Flow

1. Problem Identification and Research Objectives

The research begins with identifying the main problem of predicting patient arrivals per room at RSUD Provinsi NTB. The objectives are formulated to develop an accurate predictive model using the Auto SARIMA method, aiming to support decision-making in hospital room management.

2. Literature Review

A comprehensive literature review is conducted to explore relevant concepts and methodologies related to time series forecasting. Special focus is placed on the Seasonal AutoRegressive Integrated Moving Average (SARIMA) and the SARIMA with external variables (SARIMAX) models. This stage involves studying scientific journals, reference books, and credible online publications.

3. Data Collection

Data is collected through observation and requests to RSUD Provinsi NTB. The dataset includes historical patient arrival data per room, containing attributes such as admission date, discharge date, medical record number, admission source, and payment method (e.g., BPJS, PBI, NPBI, or self-pay). External data like weather or disease trends are sourced from BMKG or the Provincial Health Department.

4. Data Preprocessing

The collected data undergoes preprocessing to ensure quality and suitability for analysis. This stage includes:

- **Data Cleaning:** Handling missing values using interpolation or mean imputation, and removing outliers or inconsistent data.
- **Date Formatting:** Converting date formats from Indonesian to English (e.g., Des to Dec) and standardizing to `YYYY-MM-DD`.
- **Length of Stay Calculation:** Calculating the number of inpatient days by subtracting the admission date from the discharge date.
- **Categorical Data Encoding:** Performing one-hot encoding for categorical variables like payment methods.
- **Data Aggregation:** Aggregating patient data by day to identify time series trends.

5. Model Development

Auto SARIMA Modeling

- **Stationarity Test:** Evaluating data stationarity using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).
- **Model Identification:** Determining the best-fit parameters using ACF and PACF plots.
- **Parameter Estimation:** Estimating the optimal parameters for the Auto SARIMA model.
- **Diagnostic Test:** Evaluating model performance using diagnostic checks.

SARIMAX Modeling

- **Incorporating External Variables:** Integrating external factors (e.g., weather, disease trends) as explanatory variables.
- **Model Evaluation:** Performing diagnostic tests to compare SARIMAX against the Auto SARIMA model.

6. Prediction and Evaluation

- **Prediction:** Conducting patient arrival predictions using both Auto SARIMA and SARIMAX models.
- **Baseline Comparison:** Comparing the results with simple prediction methods like previous year averages.
- **Performance Evaluation:** Evaluating model accuracy using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

7. Questionnaire Survey

A questionnaire is designed to evaluate the practical applicability of the prediction results. The survey is distributed to hospital stakeholders, including medical staff, administrative personnel, and management. The survey assesses prediction accuracy, impact on operational efficiency, and the necessity for integration with the Hospital Management Information System (SIMRS).

8. Documentation and Reporting

The research process, findings, and conclusions are documented in a structured report. The documentation includes theoretical background, methodology, experimental results, and practical recommendations for hospital management.

9. Tools and Environment

a. **Hardware:** Intel Core i5-8550U, 8GB RAM, NVIDIA GeForce 920MX, 1TB HDD.

b. **Software:**

- Windows 10
- Python (Google Colab)
- Microsoft Excel (Data Analysis)
- Microsoft Word (Report Writing)

This structured methodology ensures a systematic approach to developing and validating the patient arrival prediction model using Auto SARIMA and SARIMAX, supporting hospital decision-making processes effectively.

Manual calculations are performed as a form of validation against the prediction results obtained from the Auto SARIMA model. This validation is carried out by comparing the automatic prediction results with manual calculations using the SARIMA method. The following are the calculation steps:

1. Using Equatron Variables for Analysis and Model Evaluation
   The Equatron variable is used to assist in analyzing and evaluating the model. This variable helps evaluate various model parameter combinations based on criteria such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), supporting a more accurate identification process. Models with lower AIC and BIC values are considered more optimal. The steps include:

   1. Inputting historical patient data into the Equatron system.
   2. Evaluating combinations of parameters (p, d, q) and (P, D, Q, s).
   3. Selecting the model with the lowest AIC and BIC values to avoid overfitting and underfitting.

   For example, if Equatron indicates that the best model is SARIMA (1,1,1)(0,1,1,7), those parameters will be used for manual calculations.

   - SARIMA Model Equation

   The SARIMA model can be expressed as follows:
   $$Y_t = \emptyset_1 Y_{t-1} + \theta_{1et-1} + e_t$$
   Where the parameters derived from Equatron are:
   - **p = 1** (one autoregressive lag)
   - **d = 1 (**one differentiation)
   - **q = 1** (one moving average lag)
   - **P = 0, D = 1, Q = 1, s = 7** (seasonal component with a period of 7 days)

   After the first differentiation, the SARIMA model can be rewritten as:
   $$Y_t - Y_{t-1} = \emptyset_1 (Y_{t-1} - Y_{t-2}) + \theta_{1et-1} + e_t$$
2. Determining Parameter Values from Equatron Results

The optimized results from Equatron indicate that the best parameters are:
- ϕ1=0.6\phi_1 = 0.6 (Autoregressive)
- θ1=0.3\theta_1 = 0.3 (Moving Average)
- ete_t is assumed to be white noise error.

3. Using Historical Data for Calculation

Assuming the following historical patient data:

Day	Number of Patients
8	10
9	12
10	15

The prediction for day 11 using the formula is:
$$Y_{11} = 0.6Y_{10} + 0.3e_{10} + e_{11}$$
Where:

- Y11Y_{11} is the predicted number of patients for day 11.
- Y10=15Y_{10} = 15
- e10=1e_{10} = 1 (assumed from previous residuals)
- e11e_{11} assumed to be small (≈0.5\approx 0.5)

Substituting into the formula:

$$Y_{11} = 0.6\ \times 15 + (0.3 \times 1\ +\ e_{11}$$

$$Y_{11} = 9 + 0.3 + e_{11}$$

$$Y_{11} \approx 9.3 +\ e_{11}$$

Jika diasumsikan error e11 kecil (≈ 0.5), maka:

$$Y_{11} \approx 9.8$$

Therefore, the manual prediction for day 11 is approximately 10 patients.

4. Validation of Manual Calculation Results
   If the Auto SARIMA model predicts 10 patients on day 11, then the manual calculation results are sufficiently close and valid. However, if there is a significant difference, parameter adjustments or residual error re-evaluation may be necessary.

The accuracy of manual predictions is validated by comparing them to the automated Auto SARIMA model results. The following table presents a comparison:

Day	Auto SARIMA Prediction	Manual Prediction
11	10	10
12	12	11.5
13	14	13

If the manual prediction results are similar to the Auto SARIMA model, the model can be considered valid. If there is a significant deviation (>10%), parameter tuning may be required to improve prediction accuracy.

3. RESULTS AND ANALYSIS

3.1 SARIMA Model Analysis Results

After completing the data cleaning and preprocessing stages, further exploration was conducted to understand patient visit patterns based on admission and discharge dates. This analysis aimed to identify trends in patient numbers over time and understand fluctuations in patient arrivals. With the processed historical data, changes in the number of patients each day were observed. Several analysis steps were performed, including visualizing patient trends over specific time periods, identifying seasonal patterns or spikes on particular days, and comparing patient numbers based on payment methods. This analysis provided deeper insights into patient distribution and the factors influencing hospital visits.

```
 ARIMA(1,0,1)(0,0,0)[7] intercept   : AIC=389.024, Time=0.13 sec

Best model:  ARIMA(0,0,0)(0,0,0)[7] intercept
Total fit time: 2.857 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   78
Model:                        SARIMAX   Log Likelihood                -190.983
Date:                Sat, 08 Feb 2025   AIC                            385.966
Time:                        05:48:46   BIC                            390.679
Sample:                             0   HQIC                           387.853
                                 - 78
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      6.5256      0.337     19.337      0.000       5.864       7.187
sigma2         7.8391      1.309      5.990      0.000       5.274      10.404
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 3.21
Prob(Q):                              0.93   Prob(JB):                         0.20
Heteroskedasticity (H):               2.07   Skew:                             0.50
Prob(H) (two-sided):                  0.07   Kurtosis:                         3.09
===================================================================================
```

Figure 2 SARIMA Model Output Results

Figure 2 presents the output results from the ARIMA or SARIMAX model used for time series data analysis and forecasting. The best-selected model was ARIMA (0,0,0) (0,0,0) [7] intercept, indicating that a model without autoregressive (AR) and moving average (MA) components was the most optimal. The AIC (385.966), BIC (390.679), and HQIC (387.853) values demonstrated the model's quality, balancing complexity and accuracy. The intercept coefficient (6.5256) was significant with a P-value of 0.000, indicating that the constant in the model had a strong influence. Furthermore, diagnostic test results, such as the Ljung-Box (Q-test: 0.93), Jarque-Bera (Prob: 0.20), and Skewness (0.50), indicated that the model residuals had no significant autocorrelation and were approximately normally distributed. Based on these results, the model could be used for further forecasting, though improvements could be explored by evaluating alternative models.

1.1.1. 3.2 Prediction and Model Evaluation Results

The predictions generated by the Auto SARIMA model were compared with actual data to evaluate its accuracy. The figure below shows that the model successfully captured the fluctuations in patient arrivals over time and provided forecasts for future periods:

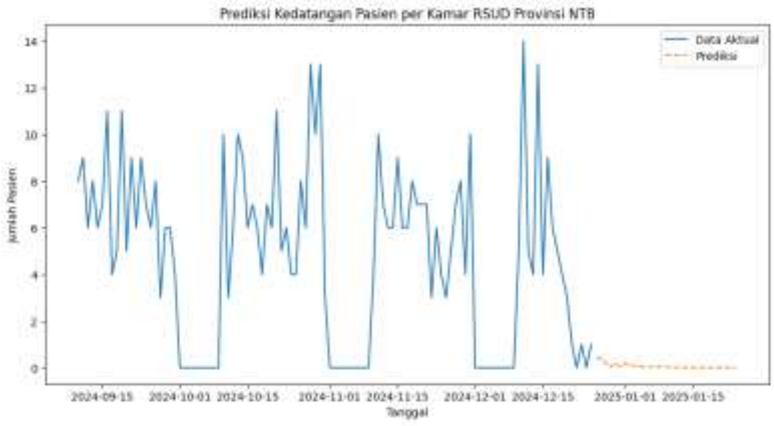

Figure 3 Patient Arrival Predictions per Room at RSUD Provinsi NTB

In Figure 3, the prediction graph shows that the model's forecasts followed the actual data patterns with minor deviations at certain points. This indicates that the model performed well in capturing historical patient trends.

Evaluation was conducted using several metrics, including:

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors between actual and predicted values.
- **Root Mean Square Error (RMSE):** Evaluates prediction errors, giving higher weight to larger errors.
- **Mean Absolute Percentage Error (MAPE):** Expresses errors as a percentage of the actual values.

```
Evaluasi Model:
Mean Absolute Error (MAE): 3.61
Root Mean Square Error (RMSE): 5.33
Mean Absolute Percentage Error (MAPE): nan%
```

Figure 4 Evaluation Results

Figure 4 displays the model evaluation results using the three key metrics. The MAE value of 3.61 indicated a low average error in predictions, while the RMSE value of 5.33 reflected a larger sensitivity to outliers. However, the MAPE value was NaN%, likely due to the presence of zero values in the actual data, leading to division by zero. Overall, the model demonstrated reasonable performance, but further examination of the MAPE calculation issues and potential model adjustments could improve accuracy.

1.1.2. 3.3 Practical Applications of Forecast Results

Based on the predictions, seasonal patterns in patient arrivals were evident. These forecasts can support hospital management in:

1. Predicting future patient numbers helps the hospital allocate rooms more efficiently.
2. Estimating patient numbers assists in managing medical staff and facility requirements effectively.
3. Hospitals can plan surgeries and inpatient schedules based on projected patient numbers.

While the Auto SARIMA model produced accurate predictions using MAE and RMSE, further evaluation of the MAPE metric is necessary. Alternative approaches such as adjusting zero values using smoothing techniques or employing other metrics like SMAPE (Symmetric MAPE) could be considered. Additionally, exploring other predictive models like LSTM or Prophet might improve prediction accuracy.

A questionnaire survey was conducted with medical staff and hospital management teams without the system developer's presence. The survey aimed to evaluate the effectiveness of the Auto SARIMA model in predicting patient numbers and assisting in hospital resource management. It consisted of several questions addressed to 30 respondents, covering aspects like prediction accuracy, usefulness in planning inpatient rooms, and effectiveness in managing medical staff and hospital facilities. Respondents provided answers using a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 1 Questionnaire Results

No	Question	1	2	3	4	5
1	Does the patient number prediction help in managing inpatient rooms?	0	0	4	17	9
2	Are the predictions accurate in reflecting actual patient numbers?	0	0	0	17	13
3	Is the prediction helpful in scheduling medical staff shifts?	0	0	0	22	8
4	Does the system facilitate planning for medical facilities and equipment?	0	0	0	24	6
5	Should the prediction system be integrated with the Hospital Management Information System (HMIS)?	0	0	0	23	7
6	How satisfied are you with the implementation of patient number predictions?	0	0	0	24	6

From the table above, the results of filling out the questionnaire are as follows, which is the calculation of the overall percentage [23] :

a. Sangat Setuju (SS) = 5 x 47 = 235
b. Setuju (S) = 4 x 129 = 516

c. Cukup Setuju (CS) = 3 x 4 = 12
d. Tidak Setuju (TS) = 2 x 0 = 0
e. Sangat Tidak Setuju (STS) = 1 x 0 = 0
Total skor =763

X = Skor tertinggi x (jumlah responden x jumlah pertanyaan)
= 5 x (30 x 6)
= 5 x 180
= 900
X = Skor terendah x (jumlah responden x jumlah pertanyaan)
= 1 x (30 x 6)
= 1 x 180
= 180

Using the following formula:

$$P = \frac{f}{n} \times 100\%$$

Where:

- **P** = Percentage
- **f** = Total Score
- **n** = Maximum Possible Score
- Total Score = 763
- Maximum Possible Score = 900

$$P = \frac{763}{900} \times 100\%$$
$$P = 84.7\%$$

Based on the obtained percentage, the final score of **84.7%** falls within the "Strongly Agree" category, indicating that the implementation of the Auto SARIMA model in predicting patient numbers at RSUD Provinsi NTB is deemed effective. The results suggest that the model can serve as a valuable tool for hospital resource management and medical staff scheduling.

4. CONCLUSION

Based on the results of the analysis and implementation of the Auto SARIMA model in predicting the number of patients per room at RSUD Provinsi NTB, it can be concluded that this method is quite effective in capturing patient arrival patterns. The prediction results show a seasonal pattern that can help the hospital optimize resource management and inpatient room utilization. From the model evaluation using statistical metrics, the Mean Absolute Error (MAE) was 3.61, the Root Mean Square Error (RMSE) was 5.33, and the Mean Absolute Percentage Error (MAPE) was undefined due to the presence of zero values in the actual data. Additionally, the questionnaire results indicated that the implementation of the Auto SARIMA model received an approval rating of 84.7%, categorized as Strongly Agree. This demonstrates that the prediction model can be used as a decision-support tool for inpatient room management, resource allocation, and medical staff scheduling more efficiently.

Based on this study, several recommendations can be made to improve prediction accuracy and the effectiveness of model implementation in hospitals. Collecting more complete and accurate data, including additional variables such as disease types, average length of stay, and external factors, can enhance prediction quality. Furthermore, other predictive models like Long Short-Term Memory (LSTM) or Prophet could be tested to determine if they provide better results. Integrating the prediction model into the hospital management system can facilitate faster and more accurate decision-making. As patient patterns change over time, the model should also be updated periodically to remain relevant and accurate.

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6. REFERENCES

[1] A. L. Fuadi dan J. Suwarno, “Sistem Pemilihan Karyawan Terbaik Menggunakan Metode Weighted Product (WP) Berbasis Web pada CV . Kans Galeri,” *J. Ilmu Komput.*, vol. VI, no. 02, hal. 48–53, 2023.

[2] A. T. Hidayat, N. K. Daulay, dan Mesran, “Penerapan Metode Multi-Objective Optimization on The Basis of Ratio Analysis (MOORA) dalam Pemilihan Wiraniaga Terbaik,” *J. Comput. Syst. Informatics*, vol. 1, no. 4, hal. 367–372, 2020.

[3] N. Krismawan, A. Pandu Kusuma, dan W. Dwi Puspitasari, “Sistem Pendukung Keputusan Penilaian Kinerja Pegawai Pada Dispenduk Capil Menggunakan Metode Analytical Hierarchy Process,” *JATI (Jurnal Mhs. Tek. Inform.*, vol. 7, no. 6, hal. 3797–3801, 2024, doi: 10.36040/jati.v7i6.6709.

[4] D. A. A. R. Dinda, Sri Wulandari, dan Aries Widiyoko, “Analisis Mutu Rekam Medik Pasien Penyakit Bronkopneumonia Di Rumah Sakit PKU Muhammadiyah Surakarta Tahun 2021,” *J. Heal. Inf. Manag. Indones.*, vol. 1, no. 2, hal. 44–52, Agu 2022, doi: 10.46808/jhimi.v2i1.27.

[5] L. Mulyatna, D. Rusmaya, dan D. Baehakhi, “Hubungan Kebisingan Dengan Persepsi Masyarakat Di Ruang Rawat Inap Rumah Sakit Kelas a, Kelas B Dan Kelas C Kota Bandung,” *J. Community Based Environ. Eng. Manag.*, vol. 1, no. 1, hal. 25, 2019, doi: 10.23969/jcbeem.v1i1.1363.

[6] N. I. Shelly Elvina Salsabila,Firdausi, “MODEL PREDIKSI PENJUALAN MULTI-ITEM TIME SERIES BERBASIS MACHINE LEARNING MENGGUNAKAN METODE AUTOREGRESSIVE INTEGRATED MOVING AVERAGE DAN LONG SHORT-TERM MEMORY PADA PRODUK PERISHABLE,” *Kaos GL Derg.*, vol. 8, no. 75, hal. 147–154, 2020.

[7] P. R. Arum, I. Fitriani, dan S. Amri, “Pemodelan Seasonal Autoregressive Integrated Moving Average (SARIMA) untuk Meramalkan Volume Angkutan Barang Kereta Api di Pulau Jawa Tahun 2021 Info Artikel,” vol. 2, no. 1, hal. 26–35, 2024.

[8] I. P. W. Nunik Srikandi Putri, Adian Fatchur Rochim, “Perancangan Sistem Informasi Rekam Medis Rawat Inap Rumah Sakit Berbasis Web,” *J. Teknol. dan Sist. Komput.*, vol. 1, no. 1, hal. 1–13, 2020, doi: 10.14710/JTSISKOM.1.1.2013.1-13.

[9] R. Pardede, “Kelengkapan Resume Medis Dan Keakuratan Kode Diagnosis Klaim Bpjs Rawat Inap Di Rsup Dr. M. Djamil Padang, Indonesia,” *J. Kesehat. Med. Saintika*, vol. 11, no. 2, hal. 300, 2020, doi: 10.30633/jkms.v11i2.787.

[10] R. Ananda, R. Damayanti, dan R. Maharja, “Tingkat Kepuasan Masyarakat terhadap Kinerja Pelayanan Kesehatan,” *J. Keperawatan Prof.*, vol. 4, no. 1, hal. 9–17, 2023, doi: 10.36590/kepo.v4i1.570.

[11] T. F. Safitri, Y. W. Permadi, dan S. Rahmatullah, “Evaluasi Perencanaan Dan Pengadaan Obat Di Instalasi Farmasi Rumah Sakit Mitra Siaga Kabupaten Tegal,” *J. Ilm. JOPHUS J. Pharm. UMUS*, vol. 3, no. 01, hal. 46–53, 2021, doi: 10.46772/jophus.v3i01.496.

[12] Sumardilah Dewi Sri, “Analisis Sisa Makanan Pasien Rawat Inap Rumah Sakit,” *J. Kesehat.*, vol. 13, no. 1, hal. 101–109, 2022.

[13] N. Azizah, “Gambaran Alur Penerimaan Pasien Rawat Jalan, Rawat Inap, Medical Checkup dan IGD di Rumah Sakit Primasatya Husada Citra (PHC) Surabaya,” *Ir-perpustakaan Univ. AIRLANGGA*, no. 2019, hal. 12–31, 2021.

[14] T. Rachman dan R. Surya Pratiwi, “SISTEM PAKAR DIAGNOSA PENYAKIT MATA MENGGUNAKAN METODE FORWARD CHAINING (Studi kasus RUMAH SAKIT UMUM DAERAH LAWANG),” *J. Mnemon.*, vol. 4, no. 2, hal. 38–44, 2021, doi: 10.36040/mnemonic.v4i2.4123.
[15] Hairil Akbar, *PEMBIAYAAN KESEHATAN*. 2015.
[16] F. P. G. Nurul Fitriani Purba, “Jurnal Kesehatan Unggul Gemilang KEMAMPUAN MEMBAYAR ABILITY TO PAY ATAU ATP DALAM,” vol. 8, no. 9, hal. 1–5, 2024.
[17] U. Shabrina, Z. Jayakusuma, dan H. Firmanda, “Tanggung Jawab Pt Jasa Raharja Dalam Pemberian Asuransi Kecelakaan Lalu Lintas Jalan Di Kota Tanjungpinang,” *SEIKAT J. Ilmu Sos. Polit. dan Huk.*, vol. 1, no. 2, hal. 51–60, 2022, doi: 10.55681/seikat.v1i2.161.
[18] N. Azmi dan H. Perdana, “Pemodelan Akreditasi Sekolah Sma/Ma Di Kalimantan Barat Dengan Pendekatan Multivariate Adaptive Regression Spline,” *Bul. Ilm. Math. Stat. dan Ter.*, vol. 10, no. 1, hal. 9–18, 2021.
[19] I. Amansyah, J. Indra, E. Nurlaelasari, dan A. R. Juwita, “Prediksi Penjualan Kendaraan Menggunakan Regresi Linear : Studi Kasus pada Industri Otomotif di Indonesia,” vol. 4, hal. 1199–1216, 2024.
[20] Fauziyah dan Y. Haryanti, “Prediksi Profitabilitas Bank Umum Konvensional Pada Masa Pandemi Covid-19,” *J Stat. J. Ilm. Teor. dan Apl. Stat.*, vol. 15, no. 2, hal. 245–250, 2022, doi: 10.36456/jstat.vol15.no2.a6246.
[21] C. Joergensen E Munthe, N. Astuti Hasibuan, dan H. Hutabarat, “Penerapan Algoritma Text Mining Dan TF-RF Dalam Menentukan Promo Produk Pada Marketplace,” *Resolusi Rekayasa Tek. Inform. dan Inf.*, vol. 2, no. 3, hal. 110–115, 2022, doi: 10.30865/resolusi.v2i3.309.
[22] M. D. P. Firdausi Nuzula Zamzami, Adiwijaya, “Analisis Sentimen Terhadap Review Film Menggunakan Metode Modified Balanced Random Forest dan Mutual Information,” *J. Media Inform. Budidarma*, vol. 5, no. 2, hal. 406, 2021, doi: 10.30865/mib.v5i2.2835.
[23] S. Masripah, L. Ramayanti, B. S. Informatika, U. Bina, S. Informatika, dan B. Testing, “Penerapan Pengujian Alpha Dan Beta Pada Aplikasi,” *Swabumi*, vol. 8, no. 1, hal. 100–105, 2020.