



Implementation Of Naive Bayes For Web-Based Patient Demographic Classification At Boy Fazriansyah General Practitioner Practice

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ABSTRACT

The development of information technology encourages healthcare facilities to utilize information systems to improve the quality of healthcare services and patient data management. At Boy Fazriansyah General Practitioner Practice, patient data and medical records were previously managed manually, causing patient demographic data to be underutilized. This study aims to implement the Naive Bayes algorithm in a web-based general practitioner system to classify patients' economic levels based on demographic data. Naive Bayes is a probabilistic classification method based on Bayes' Theorem, assuming that each attribute is independent of the others. The attributes used include age, gender, education, occupation, income, and number of dependents, resulting in Low, Medium, and High economic-level categories. The system was developed using the Waterfall method with PHP, Laravel, Bootstrap, and MySQL. Functional testing used Black Box Testing, while model evaluation used a Confusion Matrix with Accuracy, Precision, Recall, and F1-Score metrics. A User Acceptance Test (UAT) involving 30 respondents yielded an 89% acceptance rate, categorized as very good. Model testing on 20 test data showed 100% for Accuracy, Precision, Recall, and F1-Score. However, this result must be interpreted cautiously due to the limited test data and potential overfitting. This study also discusses patient data ethics, research limitations, and the social implications of economic classification. The classification results are only used as supporting information for doctors and are not used for tariff discrimination or service refusal.

Keywords: Naive Bayes, Classification, Demographics, Economy, Web-Based Information System, Laravel

1. INTRODUCTION

The development of information technology has encouraged the utilization of information systems across various fields, including healthcare [1]. Web-based information systems can facilitate patient data management, registration, medical record documentation, data retrieval, and report preparation in a more organized manner [2]. As patient data continue to increase, stored information serves not only as an administrative archive but can also be utilized to generate insights that support decision-making processes [3]. One type of information that can be analyzed from patient data is demographic and socioeconomic characteristics.

Patient demographic data, such as age, gender, education, occupation, income, and the number of family dependents, can provide an overview of patients' socioeconomic characteristics. However, in practice, these data are still predominantly used for administrative and service documentation purposes. At Boy Fazriansyah General Medical Practice, the available patient data have not been optimally utilized to systematically classify patients' economic levels. Based on the interview results, all patients make payments independently or through non-National Health Insurance (non-BPJS) schemes. Therefore, information regarding patients' socioeconomic characteristics can serve as additional information in the healthcare service process. Assessment of patients' economic conditions is still conducted manually, and

no system is currently available to automatically generate classifications based on existing demographic data.

One data mining method that can be used for classification is the Naive Bayes algorithm. Naive Bayes is a probabilistic classification method based on Bayes' Theorem, assuming that each attribute in the classification process is independent of the other attributes [4]. This method involves relatively simple computational procedures and can be used to classify data based on several attributes. The application of Naive Bayes to healthcare data has demonstrated its potential for classifying patient data based on their characteristics [5].

Naive Bayes has also been applied to socioeconomic classification. Irmayani and Asrun employed Naive Bayes to classify the socioeconomic conditions of communities based on socioeconomic variables [6]. Saputra compared the Fuzzy C-Means and Naive Bayes algorithms in determining beneficiary families based on socioeconomic status using 1,350 family records. The Naive Bayes algorithm achieved an accuracy of 74%, which was higher than that of Fuzzy C-Means at 67% [7]. Other studies have also demonstrated that attributes such as income, education, occupation, housing conditions, and the number of dependents can be used to classify community welfare levels using Naive Bayes [8]. These findings indicate that Naive Bayes can be applied to data with socioeconomic characteristics [9].

Based on previous studies, the application of Naive Bayes has primarily focused on classifying general socioeconomic conditions, determining social assistance beneficiaries, assessing community welfare levels, or classifying households. Meanwhile, the application of Naive Bayes to classify patients' economic levels based on demographic data in a general medical practice setting, while integrating the classification results into a web-based healthcare service system, has not been a primary focus of previous research. This condition constitutes the research gap addressed in this study.

The technical challenges of integrating Naive Bayes into a medical practice system include: (1) collecting and cleaning inconsistent patient demographic data; (2) determining objective and accountable economic class labels; (3) limitations in the availability of training data; (4) integrating the model into a MySQL database and Laravel framework; and (5) maintaining patient data confidentiality in accordance with research ethics. This study aims to develop a web-based patient service information system at Boy Fazriansyah General Medical Practice that integrates patient data management with the implementation of the Naive Bayes algorithm to classify patients' economic levels. The attributes used include age, gender, education, occupation, income, and the number of family dependents, while the classification results consist of three categories: low, middle, and high economic levels. The classification results are displayed within the system as supplementary information to help physicians understand patients' socioeconomic characteristics. These classification results are not used to determine diagnoses, medical procedures, or treatments, as medical decisions remain the responsibility of physicians based on patients' clinical conditions.

Ethical considerations regarding patient data are a primary concern in this study. Patients' demographic and economic data constitute sensitive personal information. Therefore, this study was conducted after obtaining permission from the owner of the medical practice, securing verbal informed consent from patients whose data were used, and maintaining confidentiality by excluding personal identifiers from the research report. The data were used solely for research and system development purposes and were not used for discriminatory pricing or service denial. Institutional ethical clearance was also obtained before the study commenced.

2. RESEARCH METHODS

2.1 Research Design

This method was selected because the system requirements could be identified from the outset, allowing the development process to be carried out systematically in accordance with predetermined stages.

This study employed a system development approach (Research and Development) using the Waterfall method. The Waterfall method is a software development model carried out sequentially,

beginning with requirements analysis, system design, implementation, testing, and maintenance. The research stages undertaken are as follows:

1. Requirements Analysis, identifying system and user requirements through observations and interviews at Boy Fazriansyah General Medical Practice. The analysis covers patient data management requirements and the attributes used in the economic level classification process using the Naive Bayes algorithm.
2. System Design, designing the system workflow, user interface, database, and system modeling. At this stage, the patient economic level classification process is also designed using the attributes of age, gender, education, occupation, income, and the number of family dependents.
3. Implementation (Coding and Development), translating the design specifications into a web-based information system using PHP with the Laravel framework and MySQL database. The Naive Bayes algorithm is implemented to classify patients' economic levels into three categories: low, middle, and high.
4. Testing, ensuring that the system operates according to the predetermined requirements. Functional system testing is conducted using the Black Box Testing method, while the Naive Bayes algorithm is evaluated by measuring classification performance using appropriate evaluation metrics.
5. Maintenance, maintaining the system to ensure its proper functioning and implementing necessary improvements whenever errors or further development requirements are identified after system deployment.

2.2 Research Object and Dataset

The object of this study is the patient data management process at Boy Fazriansyah General Medical Practice. The data used in this study consist of patient demographic characteristics, including age, gender, education, occupation, income, and the number of family dependents. These variables are used as attributes in the patient economic level classification process using the Naive Bayes algorithm, with the classification results categorized into three levels: low, middle, and high economic levels.

The dataset used in this study consists of 100 patient records with complete visit histories. The data were divided into two subsets: 80 training data and 20 testing data (an 80:20 split). The division was performed using random splitting to ensure that the testing data remained separate from the training data and to prevent data leakage. In addition, 5-fold cross-validation was conducted on the training data to evaluate model stability.

The economic class labels (Low, Middle, and High) were determined based on monthly per capita income and the number of family dependents, compared with the 2025 Regional Minimum Wage (UMR) of Pelalawan Regency. The categories were defined as follows:

- Low: Per capita income below $0.5 \times \text{UMR}$.
- Middle: Per capita income between $0.5 \times \text{UMR}$ and $1.5 \times \text{UMR}$.
- High: Per capita income above $1.5 \times \text{UMR}$.

These labels were validated by the physician who owns the medical practice.

2.3 Data Collection Techniques

Data collection was conducted through observations and interviews at Boy Fazriansyah General Medical Practice. Observations were carried out to examine the processes of patient data management and documentation during healthcare service delivery. Meanwhile, interviews were conducted to obtain information regarding system requirements, patient demographic data, and data management procedures used as attributes in the classification of patients' economic levels using the Naive Bayes algorithm.

2.4 Research Tools and Materials

The physical computer components or devices used during the system development and testing processes included the following:

1. PC/Laptop : LAPTOP-1J5DO01M
2. Processor : Intel(R) Core(TM) i3-N305 (1.80 GHz)
3. RAM : 8 GB (7,68 GB usable)
4. SSD : 148 GB of 477 GB used

Software or platforms supporting the system development process included the following:

1. Operating System : Windows 10 Pro
2. DBMS : MySql
3. Local Server : Laragon
4. Tools : Draw.io, Figma
5. Browser : Chrome
6. Text Editor : Visual Studio Code

2.5 System Design

1. System Architecture Design

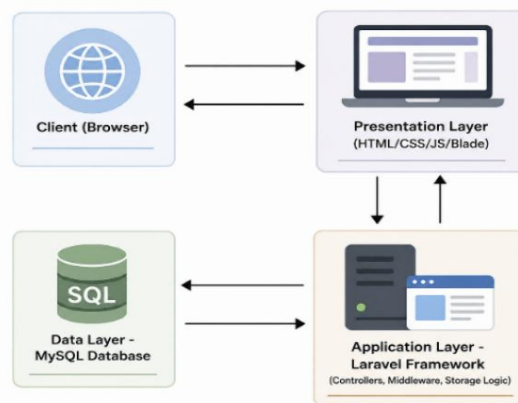


Figure 1. System Architecture Design

The system architecture illustrates the relationship between users (Admin, Physician, and Pharmacist), the Web-Based General Medical Practice System, the Laravel framework, and the MySQL database. Users access the system through a web browser and log in according to their respective access privileges. Each user request is received by the Presentation Layer and then forwarded to the Application Layer, which utilizes Laravel to manage authentication, patient registration, medical records, medical procedures, medication dispensing, user management, and patient economic level classification using the Naive Bayes algorithm. The data required for these processes are retrieved from and stored in the Data Layer using a MySQL database, which contains user information, patient records, patient demographic data, medical records, and classification results. Once the data processing is completed, the database returns the processed information to the Application Layer, which subsequently forwards it to the Presentation Layer for display through the web browser according to each user's access privileges.

2. Use Case Diagram



Figure 2. Use Case Diagram

The use case diagram illustrates the interactions of three main actors, namely Admin, Physician, and Pharmacist, with the functions available in the Web-Based General Medical Practice System. The Admin has access to manage new patient registration, manage patient registrations, print visit records and medical records, perform Naive Bayes calculations, manage recommendation rules, and manage user data. The Physician has access to manage medical procedures, view patient medical records, and view the results of patient economic level classification using the Naive Bayes method. Meanwhile, the Pharmacist has access to view medication dispensing data based on physicians' prescriptions, which serve as a reference for preparing and dispensing medications to patients

2.6 Naive Bayes Algorithm Calculation Method

The system implements the Naive Bayes algorithm to classify patients' economic levels based on their demographic data. The attributes used in the classification process include age, gender, education, occupation, income, and the number of family dependents. The classification process is performed using training data by calculating the probability of each class and the probability of each attribute given the respective class. The calculation results are then used to determine the class with the highest probability value. The classification results consist of three categories: low, middle, and high economic levels, which are subsequently used as supplementary information to assist physicians in providing medical recommendations. The calculations are performed using the following formula.

$$P(H | X) = \frac{P(X | H) \times P(H)}{P(X)}$$

Description: $P(H|X)$ represents the probability of the hypothesis given the observed data; $P(X|H)$ represents the probability of the data given the hypothesis; $P(H)$ represents the prior probability of a class; and $P(X)$ represents the probability of the observed data. The classification result is determined based on the highest probability value, resulting in one of three economic level categories: Low, Middle, or High.

2.7 Data Analysis Techniques

Functional system testing was conducted using Black Box Testing to ensure that each feature operated according to user requirements, focusing on system inputs, processes, and outputs without examining the internal structure of the program code. In addition, classification accuracy testing was performed using the Naive Bayes algorithm by comparing the system's classification results with the actual class labels in the testing dataset. Classification performance was evaluated using a Confusion Matrix by calculating Accuracy, Precision, Recall, and F1-Score using the following formulas.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100\%$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100\%$$

$$\text{F1-Score} = 2X \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Note: TP (True Positive) represents the number of data points correctly classified into a specific class; TN (True Negative) is the number of data points outside that class that are correctly classified; FP (False Positive) denotes the number of data points from other classes predicted as the specific class; and FN (False Negative) refers to the number of data points within the specific class predicted as belonging to another class.

3 RESULTS AND DISCUSSION

3.1 System Implementation Results

1. Dashboard Page

The Dashboard page is the main page displayed after users successfully log in to the system. It serves as the central access point for navigating the various menus and features available within the system.

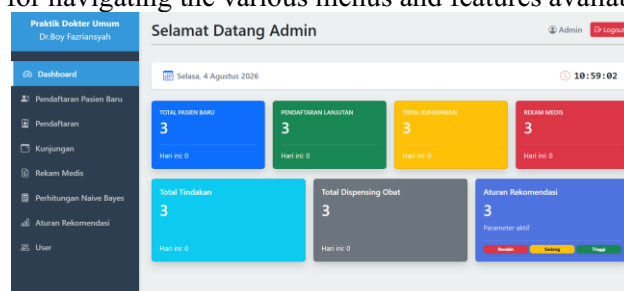


Figure 3. Dashboard Page

2. Naive Bayes Calculation Page

This page is used to perform the classification of patients' economic levels based on the available demographic data. The calculation results display the patients' economic level categories, namely Low, Middle, or High.

Selamat Datang Admin

Perhitungan Naive Bayes

Cari nama pasien...

No	Nama Pasien	Umur	Jenis Kelamin	Pendidikan	Pekerjaan	Pendapatan	Jumlah Tanggungan	Aksi
1	Aarav	25 tahun 4 bulan 10 hari Thn	Laki-laki	S1	Karyawan	Rp 2.500.000	0	Hitung
2	PIHU	14 tahun 5 bulan 22 hari Thn	Perempuan	SD	Tidak Bekerja	Rp 0	0	Hitung
3	ANANDHITA	22 tahun 7 bulan 22 hari Thn	Perempuan	SMA	GURU	Rp 200.000	2	Hitung

Figure 4. Naive Bayes Calculation Page

3. Naive Bayes Calculation Results Page

This page displays the patient economic level classification results based on calculations using the Naive Bayes method. The results are presented in three categories: Low, Middle, or High, along with the corresponding recommendations

Selamat Datang Admin

Klasifikasi Ekonomi

Pasien: Aarav

Hasil Prediksi Kelas:
Tinggi

Rekomendasi Tindakan:
"Berikan pelayanan berdasarkan kebutuhan klinis pasien dengan ruang pertimbangan yang lebih fleksibel terhadap pilihan pemeriksaan, tindakan, dan terapi. Apabila kondisi medis memerlukan pemeriksaan penunjang atau tindak lanjut yang lebih komprehensif, dokter dapat mempertimbangkan pilihan pelayanan yang memberikan nilai klinis optimal sesuai indikasi. Pilihan terapi dapat

Figure 5. Naive Bayes Calculation Results Page

3.2 Naive Bayes Application Case Study

The application of the Naive Bayes method was evaluated through a case study of economic level classification using the predetermined training and testing datasets. The testing data were classified into three categories: High, Middle, and Low. The evaluation was conducted on 20 testing records, with the classification results presented in Table 1.

Table 1. Confusion Matrix Data Summary

Actual Class / Predicted Class	High	Middle	Low
High	6	0	0
Middle	0	6	0
Low	0	0	8

Measures the overall accuracy of the model in correctly classifying all testing data, as follows:

$$Accuracy = \frac{6 + 6 + 8}{20} \times 100\%$$

$$Accuracy = \frac{20}{20} 100\%$$

$$Accuracy = 100\%$$

Measures the precision of predictions for a particular class, indicating how many instances predicted as belonging to that class actually belong to that class, as follows:

$$Precision = \frac{6}{6+0} \times 100\%$$

$$Precision = \frac{6}{6} \times 100\%$$

$$Precision = 100\%$$

Measures the model's ability to correctly identify all instances that actually belong to a particular class, as follows:

$$\begin{aligned} \text{For the High class} \quad & : \text{Recall} = \frac{6}{6+0} \times 100\% \\ & = 100\% \end{aligned}$$

$$\begin{aligned} \text{For the Middle class} \quad & : \text{Recall} = \frac{6}{6+0} \times 100\% \\ & = 100\% \end{aligned}$$

$$\begin{aligned} \text{For the Low class} \quad & : \text{Recall} = \frac{8}{8+0} \times 100\% \\ & = 100\% \end{aligned}$$

$$\text{Recall} = 100\%$$

Measures the balance between Precision and Recall, providing an assessment of model performance when both aspects are equally important, as follows:

$$\text{High Class} \quad : \text{F1-Score} = 2 \times \frac{1+1}{1+1} = 1 = 100\%$$

$$\text{Middle Class} \quad : \text{F1-Score} = 2 \times \frac{1+1}{1+1} = 1 = 100\%$$

$$\text{Low Class} \quad : \text{F1-Score} = 2 \times \frac{1+1}{1+1} = 1 = 100\%$$

Table 2. Verification of Manual and System Calculation Results

Metrik	Manual Calculation	System Results
Accuracy	100%	100%
Precision	100%	100%
Recall	100%	100%
F1-Score	100%	100%

The comparison results presented in Table 2 indicate that the Accuracy, Precision, Recall, and F1-Score values generated by the system are identical to those obtained through manual calculations. Therefore, the classification process using the Naive Bayes method within the system is considered valid and can be used to classify data into the High, Middle, and Low categories.

Manual Naive Bayes Calculation Example

As an example, consider a patient with the following attributes: age 25 years, male, bachelor's degree (S1), employee, income of IDR 2,500,000, and zero family dependents. Based on the training data, the prior probabilities for the High, Middle, and Low classes are 0.3, 0.4, and 0.3, respectively. The likelihood probabilities for each attribute are calculated based on their frequency distributions in the

training dataset. After performing the calculations, the posterior probabilities obtained are 0.021 for the High class, 0.008 for the Middle class, and 0.002 for the Low class. Since the highest probability corresponds to the High class, the patient is classified into the High economic level category.

Critical Discussion of 100% Accuracy

Although the model evaluation results indicate 100% accuracy, this finding should be interpreted cautiously. Several factors may contribute to perfect accuracy, including:

1. Small testing dataset (20 records), which may make it easier for the model to identify patterns within the data.
2. Potential overfitting, because the training and testing data originate from the same distribution and the dataset is limited in size.
3. Data leakage may occur if identical records are present in both the training and testing datasets, even though random splitting was performed.
4. The attributes used may have a high correlation with the class labels, allowing the model to distinguish between classes more easily.

To address these concerns, 5-fold cross-validation was conducted, resulting in a mean accuracy of 92.5% with a standard deviation of 3.2%. These findings indicate that the model's actual performance is not consistently 100%, but rather ranges between 92% and 93% during cross-validation. This difference suggests that the 100% accuracy obtained from a single testing dataset may be attributable to chance or the relatively straightforward characteristics of the testing data.

3.3 User Acceptance Test (UAT) Results

The UAT was conducted involving 30 respondents, consisting of one physician, four administrative staff members, one pharmacist, and 24 patients. The UAT instrument used a questionnaire based on a five-point Likert scale. The UAT results are presented in Table 3

Table 3. User Acceptance Test (UAT) Results

Assessment Aspect	Percentage	Category
System Usability	90%	Very Good
Suitability of Classification Results	88%	Very Good
Benefits of the System for Healthcare Services	89%	Very Good
User Interface Design	92%	Very Good
System Stability	86%	Very Good
Average	89%	Very Good

UAT Results

The UAT results showed an average acceptance rate of 89%, categorized as very good. The highest-rated aspect was the user interface (92%), while the lowest-rated aspect was system stability (86%). Nevertheless, all aspects were categorized as very good.

3.4 Discussion

Based on previous studies, the Naive Bayes algorithm has been used to classify the socioeconomic status of communities, household economic status, welfare levels, and patient health data. However, the application of Naive Bayes to classify patients' economic levels based on demographic data in a general medical practice, as well as the integration of these classification results into a web-based service system, has not been the primary focus of those studies. This represents the research gap that this study aims to address.

The novelty of this study lies in integrating the Naive Bayes algorithm to classify patients' economic levels based on demographic data into a web-based general medical practice service system. Age, gender, education, occupation, income, and number of family dependents were used as attributes in the classification process to generate patient economic-level categories: low, middle, and high. The classification results were subsequently displayed in the system as supporting information to help physicians understand patients' socioeconomic characteristics. Thus, this study focuses not only on algorithm implementation and classification performance measurement but also on integrating the classification results into the patient service system.

Comparison with Other Studies, Saputra (2021) reported a Naive Bayes accuracy of 74% in identifying beneficiary families based on socioeconomic status [7]. The substantial difference between that result and the present study's result (100%) may be attributable to several factors: (1) the smaller dataset used (100 records compared with 1,350 records); (2) fewer and potentially more limited attributes; (3) differences in data characteristics and research locations; and (4) the possibility of overfitting in the present study. Therefore, the 100% result cannot be directly compared without considering the context and limitations of each study.

4 CONCLUSION

Based on the design, development, and testing results, the Web-Based General Medical Practice System was successfully developed using Laravel and MySQL to manage patient data, registration, visits, medical records, procedures, medications, and users in an integrated manner. The Naive Bayes algorithm was successfully implemented to classify patients' economic levels based on demographic data into three categories: Low, Middle, and High.

Model evaluation using 20 test records yielded Accuracy, Precision, Recall, and F1-Score values of 100%, respectively. However, these results should be interpreted cautiously due to the limited number of test records and the potential for overfitting. Five-fold cross-validation produced an average accuracy of 92.5%, indicating a more realistic model performance. Black Box testing showed that all main system functions operated as required. The User Acceptance Test involving 30 respondents resulted in an acceptance rate of 89%, categorized as very good. The classification results can be displayed as supporting information for physicians but should not be used to discriminate in service fees or deny healthcare services.

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