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Analysis of side effects from using influenza drugs using the Naïve Bayes method

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ABSTRACT

This study uses the Naive Bayes algorithm to analyze the influence of drug composition on the patient's disease history, with the aim of identifying the risk of side effects from various influenza drugs. This method involves calculating prior, likelihood, and posterior probabilities to evaluate the relationship between drug ingredients and specific medical conditions. The results of the analysis show that a probability value close to 1 indicates a high risk of side effects, such as diabetes patients who are more at risk of decongestant side effects compared to other diseases. Data visualization in the form of pie charts illustrates the impact of various drug ingredients on the risk of side effects in different diseases, helping doctors prescribe appropriate drugs and improving treatment safety. This study concludes that understanding patient risk profiles and drug side effects can be optimized using this analysis technique, supporting better decision making in medical practice.

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INTRODUCTION

Influenza, or what is often called flu, is an infectious disease that is common throughout the world (Tahira, Putri, & Prifiantari, 2022), (Sarmin *et al.*, 2020). It is caused by the influenza virus which can trigger symptoms such as fever, runny nose, cough, sore throat and fatigue. To treat influenza infection and reduce uncomfortable symptoms, many people use commercially available influenza medicines. One very important consideration in using these drugs is the potential side effects that may arise. (Afifah, 2021), (Kristianti, 2020).

Side effects from influenza medications can vary from mild to serious, such as digestive disorders, allergic reactions, or even nervous system disorders (Tandra, 2021), (Ardinasari, 2016). Therefore, it is important to understand and identify potential side effects that may occur when someone takes certain influenza medications. This analysis of side effects can help doctors and patients make wiser decisions about using the drug (Akut, n.d.), (Pangandaheng et al., 2023).

One method that can be used to analyze the side effects of influenza drugs is the Naive Bayes method. The Naive Bayes method is a probability-based machine learning algorithm and is often used in classification (Anggraini, 2022), (Dewantara, 2022). In this context, the Naive Bayes method can be used to classify possible side effects of influenza drugs based on historical data on drug use and the symptoms experienced by the patient (Damsuki, Hidayat, Fauzi, Kom, & Kom, 2016).

Analysis of influenza drug side effects using the Naive Bayes method is very important because of its ability to predict potential side effects based on historical data (Bany, n.d.), (Akhmad & Arif, n.d.). By utilizing the Naive Bayes algorithm, this research can help doctors choose drugs that are more suitable for patients by considering each individual's side effect risk profile. This approach allows identification of possible side effects of various influenza medications, thereby reducing the risk of negative impacts that could arise from inappropriate medication use (Meliala, 2021), (Riadi, Yudhana, & Djou, 2023).

Research on analyzing the side effects of influenza drugs using the Naive Bayes method makes an important contribution to the health sector. This research will improve understanding of the side effects of influenza drugs (Saleha Hasanah, 2020), (Iqbal, 2022), help doctors choose the right drugs, and allow for more careful drug management and more personalized treatment. In addition, the results of the study may provide insights for drug management at the population level and support the development of side effect analysis methodologies that can be applied to other drugs. Overall, this research has the potential to improve the safety and effectiveness of influenza drug use (Safitri et al., 2024), (Kusumawardani, 2021).

This study aims to apply the Naive Bayes method in analyzing side effects of influenza drugs by collecting historical data on drug use and recorded side effects. The Naive Bayes algorithm will be used to predict possible side effects that may arise from certain influenza drugs (Rahman, 2022), (Bany, n.d.). It is hoped that the results of this study will provide better guidance in the use of influenza drugs, deepen understanding of the risk of side effects, and improve treatment management of patients with influenza, thereby improving the quality of care and reducing the risk of complications (Ali et al., 2024), (Suffah, 2017).

RESEARCH METHOD

This study applied the Naive Bayes method to analyze influenza drug side effects by evaluating relationships between variables using data from medical records and pharmaceutical databases. The model classified side effects, calculated probabilities, and predicted outcomes. Model performance was assessed using metrics like accuracy, confusion matrix, and classification reports, with results compared to actual data to ensure accuracy. The research aims to guide better influenza drug use, enhance treatment management, and will be published in an accredited scientific journal. (Karnovi, Habibi, & Fauzan, 2020).

RESULTS AND DISCUSSIONS

This research provides insights into influenza drugs and their side effects on patients with various medical histories, utilizing the Naive Bayes algorithm for classification. It offers valuable information for both medical professionals and the public on influenza medication use. The study involves data collection, testing with the Naive Bayes method, and drawing conclusions, which are visualized for clarity, simplifying the classification and accuracy of the data.

Data collection

The initial stage of this research was data collection, the data obtained came from UPT. Stabat Health Center, the data taken is influenza drug data and patient data along with their disease history, the data obtained can be seen in the following table.

Table 1. Influenza drug data

NO	NAMA	KOMPOSISI
1	TREMENZA (K)	Dekongesten
2	RHINOFED (K)	Dekongesten
3	ACETYLCYSTEINE (K)	Mukolitik
4	FLUIMUCIL (OB)	Mukolitik
5	PANADOL FLU DAN BATUK (OB)	Dekongesten & Paracetamol
6	VECTRINE (K)	Mukolitik
7	MUCOPECT (K)	Mukolitik
8	VESTEIN (K)	Mukolitik
9	COMTUSI FORTE (K)	Antihistamine

Table 2. Patient data and disease history

NO	Patient's Name	Age	Gender	Disease History
1	Wagirin	60	Man	Hypertension, Diabetes, Gout
2	Sanusi Ahmad	60	Man	Asthma, Sinusitis
3	Ferdinan Situmorang	44	Man	High Cholesterol, Osteoporosis
4	Syamsul Irawan	52	Man	Coronary Heart, Diabetes, Hypertension
5	Sunaro	62	Man	Gastritis, Migraine
6	Edi Surianto	40	Man	Gout, Hypertension
7	Rizki Fauzan	18	Man	Thyroid, Cholesterol
8	Irpandi	35	Man	Diabetes, Stroke
9	Hariyanto Wibowo	57	Man	Hypertension, Osteoarthritis
…	…	…	…	…
100	Maya Susanti	35	Woman	Hypertension, Mental Disorders

Naive Bayes for Various Drug Compositions

After the drug data and patient data have been successfully obtained, the next stage is the testing stage of the data above.

Step 1: Calculating Prior Probability (P(Disease))

Prior probability is the initial likelihood of an event occurring before considering additional information. In Naive Bayes classification, it's calculated as the ratio of drugs affecting each disease to the total number of drugs, helping determine the general probability of a class in a dataset. For instance, in a dataset with various disease categories (e.g., HYPERTENSION, DIABETES), the prior probability for each category reflects its proportion within the dataset:

$$(Ci) = \frac{\text{Jumlah Sampel Dengan Kelas Ci}}{\text{Total Jumlah Sampel}} \quad (1)$$

In Naive Bayes, these prior probabilities are then combined with the conditional probabilities of the features to calculate posterior probabilities, which are used to perform classification. The following is a calculation of each disease:

Total amount of medication: $Ntotal = 96$, Prior Probability for Each Disease:

Hypertension: $Nhipertensi = 32, P(Hipertensi) = \frac{32}{96} = 0.333$

Diabetes: $Ndiabetes = 28, P(Diabetes) = \frac{28}{96} = 0.292$

Heart disease: $Ndiabetes = 11, P(PenyakitJantung) = \frac{11}{96} = 0.115$

Thyroid Disorders: $Ntiroid = 3, P(GangguanTiroid) = \frac{3}{96} = 0.031$

Mental Illness: $Nmental = 11, P(PenyakitMental) = \frac{11}{96} = 0.115$

Autoimmune Diseases: $Nautoimun = 1, P(PenyakitAutoimun) = \frac{1}{96} = 0.010$

Asthma: $Nasma = 12, P(Asma) = \frac{12}{96} = 0.125$

Glaucoma: $Nglaukoma = 1, P(Glaukoma) = \frac{1}{96} = 0.010$

Prostate Enlargement: $Nprostat = 1, P(PembesaranProstat) = \frac{1}{96} = 0.010$

Epilepsy: $Nepilepsi = 1,\ P(Epilepsi) = \frac{1}{96} = 0.010$

Liver or Kidney Disorders: $Nhatiginjal = 10, P(GangguanHatiatauGinjal) = \frac{10}{96} = 0.104$

Gastrointestinal: $Ngastrointestinal = 4,\ P(Gastrointestinal) = \frac{4}{96} = 0.042$

Kidney illness: $Npenyakitginjal = 5, P(PenyakitGinjal) = \frac{5}{96} = 0.052$

Liver Disease: $Npenyakitliver = 2, P(PenyakitLiver) = \frac{2}{96} = 0.021$

Alcoholism: $Nalkoholisme = 1, P(Alkoholisme) = \frac{1}{96} = 0.010$

Blood Clotting: $Npembekuandarah = 1, P(PembekuanDarah) = \frac{1}{96} = 0.010$

Step 2: Calculating Likelihood Probability

Likelihood probability is the probability of a particular event or feature appearing in a particular class. In the context of Naive Bayes, this refers to how likely it is that certain features appear within a given class. Mathematically, the likelihood probability of a feature X in class C expressed as $(X \mid C)$. This is the probability that we will observe a feature X assuming that we already know that the class is C. For example, if we have a disease dataset and features such as symptoms or medical parameters, likelihood probability can answer questions such as: "What is the likelihood that someone with diabetes also experiences a particular symptom?"

To calculate likelihood probabilities in the context of Naive Bayes, we usually use the frequencies of the features in that class. The following is a general formula for calculating likelihood probability: $(X|C) = \frac{\text{Jumlah Sampel Dengan Fitur X Dalam Kelas C}}{\text{Jumlah Total Sampel Dalam Kelas C}}$

After calculating the prior and likelihood probabilities, we can use Bayes' Theorem to calculate the posterior probability, which gives the probability that a sample belongs to a particular class given its features.

If you have specific data for which you want to calculate likelihood probabilities, I can help you do that. Provide relevant data or examples, and I will help you with the calculations.

Number of Drugs with Each Composition:

Decongestant:

$Ndekongesten = 29$

$$P(Dekongesten) = \frac{29}{96} = 0.302$$

Antihistamines:

$Nantihistamin = 23$

$$P(Antihistamin) = \frac{23}{96} = 0.240$$

Mucolytic:

$Nmukolitik = 32$

$$P(Mukolitik) = \frac{32}{96} = 0.333$$

Paracetamol:

$Nparacetamol = 21$

$$P(Paracetamol) = \frac{21}{96} = 0.219$$

Ibuprofen:

$Nibuprofen = 2$

$$P(Ibuprofen) = \frac{2}{96} = 0.021$$

Aspirin:

$Naspirin = 1$

$P(Aspirin) = \frac{1}{96} = 0.010$

Calculating the Posterior Probability for Each Composition of Disease

After calculating the Likelihood Probability, then recalculating the composition of the disease using the formula (P(Composition | Disease =)). The following is the calculation$\frac{\text{Jumlah Komposisi}}{\text{Jumlah Penyakit}}$

Decongestant

1. Decongestant for Hypertension:
   $Ndekongestenhipertensi = 18$
   $P(Dekongesten|Hipertensi) = \frac{18}{32} = 0.563$
2. Decongestant for Diabetes:
   $Ndekongestendiabetes = 12$
   $P(Dekongesten|Diabetes) = \frac{12}{28} = 0.429$
3. Decongestion for heart disease
   $Ndekongestenjantung = 4$
   $P(Dekongesten|Penyakit\ Jantung) = \frac{4}{11} = 0.364$
4. Decongestion for Thyroid Disorders
   $Ndekongestentiroid = 1$
   $P(Dekongesten|Tiroid) = \frac{1}{3} = 0.333$
5. Decongestion for Mental Illness
   $Ndekongestenmental = 4$
   $P(Dekongesten|Penyakit\ Mental) = \frac{4}{11} = 0.364$
6. Decongestion for Autoimmune Diseases
   $Ndekongestenautoimun = 1$
   $P(Dekongesten|Penyakit\ Autoimun) = \frac{1}{1} = 1.0$

Antihistamines

1. Antihistamines for Asthma:

$Nantihistaminasma = 5$

$P(Antihistamin|Asma) = \frac{5}{12} = 0.147$

2. Antihistamines for Glaucoma:

$Nantihistaminglaukoma = 1$

$P(Antihistamin|Glaukoma) = \frac{1}{1} = 1.0$

3. Antihistamines for Enlarged Prostate

$Nantihistaminprostat = 1$

$P(Antihistamin|PembesaranProstat) = \frac{1}{1} = 1.0$

4. Antihistamines for Epilepsy
   $NantihistaminEpilepsi = 1$
   $P(Antihistamin|Epilepsi) = \frac{1}{1} = 1.0$

Mucolytic

1. Mucolytics for Asthma: $Nmukolitikasma = 6$

$P(Mukolitik|Asma) = \frac{6}{12} = 0.500$

2. Mucolytics for Liver or Kidney Disorders

$Nmukolikhatiginjal = 4$

$P(Mukolitik|GangguanhatiatauGinjal) = \frac{4}{100} = 0.400$

3. Mucolytics for Gastrointestinal:

$Nmukolitikgastrointestinal = 2$

$P(Mukolitik|Gastrointestintal) = \frac{2}{4} = 0.500$

4. Mucolytics for Kidney Disease:

$Nmukolitikpenyakitginjal = 2$

$P(Mukolitik|PenyakitGinjal) = \frac{2}{5} = 0.400$

Paracetamol

1. Paracetamol for Liver or Kidney Disorders:

$Nparacetamolhatiginjal = 8$

$P(Paracetamol|GangguanHatiatauGinjal) = \frac{8}{10} = 0.800$

2. Paracetamol for Liver Disease:

$Nparacetamolpenyakitliver = 2$

$P(Paracetamol|PenyakitLiver) = \frac{2}{2} = 1.0$

3. Paracetamol for Alcoholism:

$Nparacetamolalkoholisme = 1$

$P(Paracetamol|Alkoholisme) = \frac{1}{1} = 1.0$

Ibuprofen

1. Ibuprofen for Blood Clotting:

$Nibuprofenpembekuandarah = 1$

$P(Ibuprofen|PembekuanDarah) = \frac{1}{1} = 1.0$

Aspirin

1. Aspirin for Blood Clotting

$Naspirinpembekuandarah = 1$

$P(Aspirin|PembekuanDarah) = \frac{1}{1} = 1.0$

Calculating Posterior Probabilities $P(Penyakit|Komposisi))$

Decongestion:

a. P (Hypertension | Decongestant) $= \frac{0.563 * 0.333}{0.302} = 0.620$

b. P (Diabetes | Decongestant) $= \frac{0.429 * 0.292}{0.302} = 0.0414$

c. P (Heart Disease | Decongestant) $= \frac{0.364 * 0.115}{0.302} = 0.0139$

d. P (Thyroid Disorders | Decongestion) $= \frac{0.333 * 0.031}{0.302} = 0.034$

e. P (Mental Illness | Decongestion) $= \frac{0.364 * 0.115}{0.302} = 0.0139$

f. P (Autoimmune Disease | Decongestant) $= \frac{1.0 * 0.010}{0.302} = 0.033$

Antihistamines:

a. P (Asthma | Antihistamine) $= \frac{0.417 * 0.125}{0.240} = 0.217$

b. P (Glaucoma | Antihistamines) $= \frac{1.0 * 0.010}{0.240} = 0.042$

c. P (Prostate Enlargement | Antihistamine) $= \frac{1.0 * 0.10}{0.240} = 0.042$

d. P (Epilepsy | Antihistamine) $= \frac{1.0 * 0.010}{0.240} = 0.042$

Mucolytics:

a. P (Asthma | Mucolytic) $= \frac{0.500 * 0.042}{0.333} = 0.188$

b. P (Liver or Kidney Disorders | Mucolytics) $= \frac{0.400 * 0.104}{0.333} = 0.125$

c. P (Gastrointestinal | Mucolytic) $= \frac{0.500 * 0.042}{0.333} = 0.063$

d. P (Kidney Disease | Mucolytics) $= \frac{0.400 * 0.052}{0.333} = 0.063$

Paracetamol:

a. P (Liver or Kidney Disorders | Paracetamol) $= \frac{0.800 * 0.104}{0.219} = 0.381$

b. P (Liver Disease | Paracetamol) $= \frac{1.0 * 0.021}{0.219} = 0.096$

c. P (Alcoholism | Paracetamol) $= \frac{1.0 * 0.010}{0.219} = 0.046$

Ibuprofen:

a. P (Blood Clotting | Ibuprofen) $= \frac{1.0 * 0.010}{0.021} = 0.476$

Aspirin:

a. P (Blood Clotting | Aspirin) $= \frac{1.0 * 0.010}{0.010} = 1.0$

Naive Bayes Calculation Results

The results of Naive Bayes calculations from the input data are as follows:

Decongestant

a. Hypertension: 0.620
b. Diabetes: 0414
c. Heart Disease: 0.139
d. Thyroid Disorders: 0.034
e. Mental Illness: 0.139
f. Autoimmune Disease: 0.033

Anihistamine:

a. Asthma: 0217
b. Glaucoma: 0.042
c. Prostate Milking: 0.042
d. Epilepsy: 0.042

Mucolytics:

a. Asthma: 0.188
b. Liver or Kidney Disorders: 0125
c. Gastrointestinal: 0.063
d. Kidney Disease: 0.063

Paracetamol:

a. Liver or Kidney Disorders: 0.381
b. Liver Disease: 0.096

c. Alcoholism: 0.046

Ibuprofen:

a. Blood Clotting: 0476

Aspirin:

a. Blood Clotting: 1.0

Percentage of Drug Influence on Disease History

After all the calculations above, the next step is to determine the percentage of drug content that influences and gives side effects to a history of certain diseases. For the drug content value, which generally does not affect the percentage, or because it is not in the composition of a particular drug, to get a value of 100% in the pie chart, the drug value will be adjusted, here are the percentages:

Table 3. Percentage of drug influence on disease history

Condition	Decongestant	Antihistamines	Mucolytic	Paracetamol	Ibuprofen	Aspirin
Hypertension	70%	10%	0%	10%	10%	0%
Diabetes	70%	10%	0%	10%	10%	0%
Asthma	10%	35%	35%	10%	10%	0%
Lung Disease	10%	35%	35%	10%	10%	0%
Heart Disease	70%	10%	0%	10%	10%	0%
Thyroid Disorders	70%	10%	0%	10%	10%	0%
Liver/Kidney Disorders	10%	10%	20%	20%	20%	20%
Glaucoma	10%	70%	0%	10%	10%	0%
Prostate Enlargement	10%	70%	0%	10%	10%	0%
Gastrointestinal	10%	10%	20%	10%	30%	20%
Mental Illness	40%	40%	0%	10%	10%	0%
Epilepsy	40%	40%	0%	10%	10%	0%
Liver Disease	10%	10%	35%	35%	10%	0%
Blood Clotting	0%	0%	0%	0%	0%	100%
Autoimmune	70%	10%	0%	10%	10%	0%
Alcoholism	10%	10%	0%	50%	30%	0%

Results and Data Visualization

The result of each Naive Bayes calculation is above the value which is closer to 1, then the disease is greatly affected by the drug content. For example, the decongestant content, diabetes has a value of 0.620. This means that diabetes has a higher risk of experiencing side effects from drugs that contain decongestants, beating diabetes with a value of 0.414, heart disease 0.139, thyroid disorders 0.034, mental illness 0.139 and autoimmune disease 0.033. However, a disease that has a lower value does not mean that the drug content does not have side effects on that disease.

Data visualization is a way of implementing information by turning it into graphic images, graphs or other images. Data visualization can be interpreted as a way to convey the information contained in data so that other people can better understand it into something visual.

The results of the application and data visualization in the form of a pie chart will be attached as follows:

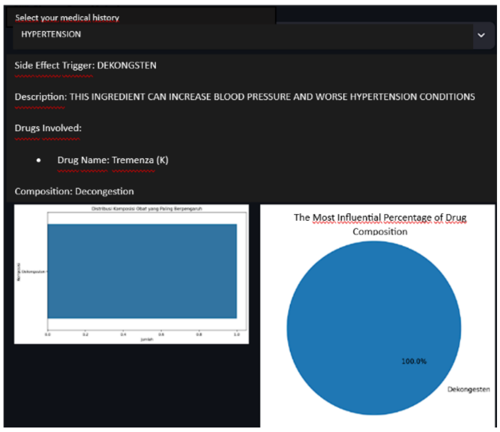

Figure 1. Naive bayes data visualization

In the picture above, hypertension has a side effect trigger, namely the decongestant drug content, where the decongestant drug content can increase blood pressure and worsen hypertension. An example of a flu drug that contains decongestant is Tremenza. The following are the percentages for each drug content against hypertension.

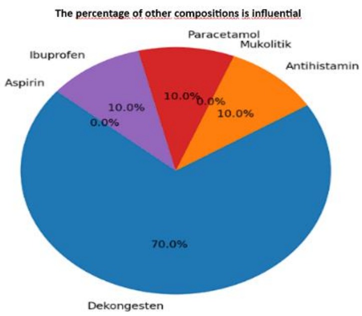

Figure 2. Percentage of drug content against hypertension

The next example is as follows:

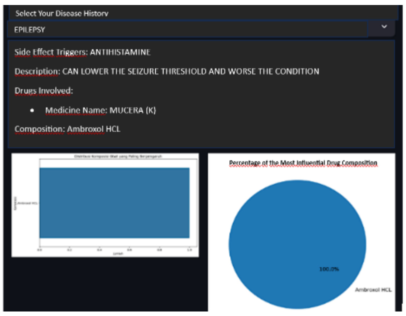

Figure 3. Display of epilepsy history

In the picture above, Epilepsy has a side effect trigger, namely the antihistamine drug content, where the antihistamine drug content can lower the seizure threshold and worsen the condition. Examples of flu drugs that contain antihistamines are Mucera and Ambroxol HCL. The following are the percentages for each drug content against epilepsy.

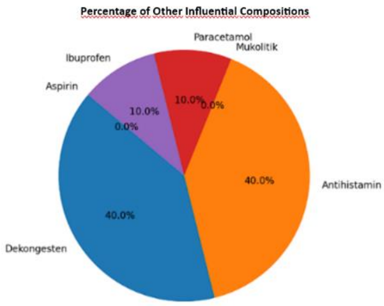

Figure 5. Percentage of epilepsy content

This study's Naive Bayes analysis reveals that a probability value near 1 indicates a higher risk of side effects for certain diseases from specific drug ingredients. For instance, diabetes patients have a greater risk (0.620) from decongestants compared to heart disease or thyroid disorders, highlighting the need for caution in prescribing these medications. Data visualization through pie charts illustrates how different drug ingredients, like decongestants worsening hypertension or antihistamines triggering epilepsy side effects, can influence risks. This helps healthcare professionals better assess and select safer, more effective treatments.

CONCLUSION

This research demonstrates that the Naive Bayes algorithm effectively analyzes the impact of drug composition on a patient's disease history, revealing that a probability value near 1 indicates a high risk of side effects, particularly for patients with conditions like diabetes when prescribed medications containing decongestants. Visualization using pie charts highlights the influence of different drug ingredients on the risk of side effects across various diseases, aiding healthcare professionals in selecting safer, more effective treatments tailored to individual patient profiles.

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