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COMPARING MODEL OF BEST FIT FOR CLINICAL DECISION SUPPORT SYSTEM FOR THE MANAGEMENT OF DIPHTHERIA DISEASE

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Abstract: **The use of Artificial Intelligence in medical diagnosis is becoming increasingly common and has been used widely in the diagnosis of cancers, tumors, diphtheria, hepatitis, lung diseases, etc. Diphtheria Disease is a chronic health problem with devastating, yet preventable consequences. Due to this shortage of specialists, there is a need for a Clinical Decision Support System that will diagnose and manage diphtheria disease. This work is therefore aimed at designing a web-based Clinical Decision Support System for the management of early diphtheria disease. Four pattern classification algorithms (K-nearest neighbor, Decision Tree, Decision Stump and Rule Induction) were adopted in this study and were evaluated to choose the most precise algorithm to be employed in the developed clinical decision support system. The evaluation was carried out on appropriate dataset that was obtained from Babcock University Teaching Hospital and the University of Port Harcourt Teaching Hospital. The following benchmarks were used in comparing the generated models: performance, accuracy level, precision, confusion matrices and the model's building's speed. From the model comparison, the study showed that Naïve Bayes outperformed all other classifiers with accuracy being 60.50%. k-nearest neighbour, Decision Tree, Decision Stump and Rule induction perform well with the lowest accuracy for x- cross validation being 36.50%. Decision Tree falls behind in accuracy, while k-nearest neighbour and Decision Stump maintain accuracy at equilibrium 41.00%. Therefore, Naïve Bayes is adopted as optimal algorithm in the domain of this study.**

Keywords: **Decision Stump, Diphtheria, k-nearest neighbour, Naïve Bayes, Rule induction.**

1. INTRODUCTION

Fever, a painful throat, and swelling of the lymph nodes in the neck are some of the first signs of diphtheria. The typical incubation time is between 1 and 10 days, with the average being around 5 days. Since early 2023, the diphtheria outbreak in Nigeria has been frightening, and it spiked in March of that year. From week 1 of 2023 to week 4 of 2023, there was an increase from 136 to 253 suspicious cases recorded. The Nigeria Centre for Disease Control (NCDC) has reported yet another spike in cases as of March 2nd, 2023. Children under the age of 18 make up the largest proportion of the 733 confirmed cases and 89 fatalities (CFR 12.3%). Overall, 12.3 percent of cases result in death. According to the most up-to-date information from ProMed shared with the WHO, suspected cases have been reported in 20 different states across Nigeria, with the vast majority of cases coming from the states of Kano (74%), Yobe (12%), Katsina (6%), Sokoto (2%), Enugu (1%), Ogun (1%), Osun (1%), Kaduna (1%), Lagos (1%), and Zamfara (1%) respectively. There are many unvaccinated youngsters in Osun and Lagos States, putting them at danger for contracting diphtheria. This diphtheria epidemic has been called the worst in Nigeria in recent times.

Notwithstanding the widespread prevalence of diphtheria in unvaccinated populations, just 27 of 216 confirmed cases (12.5%) were found to have received a complete dose of a vaccination containing diphtheria toxin, according to the National Centre for Disease Control and Prevention. The NCDC is working with state health agencies and partners to enhance monitoring and response to the epidemic, which includes laboratory-confirmed as well as clinically suspected cases. The NCDC has been collaborating with affected parties to raise awareness of the illness, but the number of reported cases is rising. On December 1st, 2022, NCDC received reports of possible diphtheria infections in the states of Kano and Lagos. The first confirmed instances of a diphtheria epidemic occurred in the states of Lagos and Kano, and on January 20, 2023, the Nigeria Centre for Disease Control and Prevention (NCDC) labeled the situation an outbreak. The geographic range of diphtheria expanded rapidly. To coordinate the reaction on all fronts, the Emergency Operations Centre (EOC) of the National technical working group was created. The government has appealed to national states for help in increasing immunizations in light of the worrying trend.

Diphtheria may affect the lungs or the skin. The nose, throat, and tonsils are affected by respiratory diphtheria, whereas the skin is affected by cutaneous diphtheria. There is a common thread that runs across every dipthetria. Diphtheria is a life-threatening bacterial infection of the nasal and throat membranes. Corynebacterium diphtheriae is the causative agent of the diphtheria infection. While most cases of this illness are asymptomatic or have a mild clinical course, in rare outbreaks, death rates of over 10% have been reported. Symptoms, which may range in severity from none to severe, often manifest themselves between two- and five-days following exposure. Typical early symptoms include a high temperature and a sore throat. When it becomes bad enough, a grey or white patch might appear in the neck. This may cause a barking cough, similar to that of croup, by blocking the airway. The lymph nodes in the neck may swell and cause the neck to swell. Myocarditis, inflammation of the nerves, renal issues, and bleeding issues from low platelet counts are all possible complications. Inflammation of the nerves may cause paralysis, and myocarditis can cause an irregular heartbeat. Diphtheria is very contagious, but immunisations are available to prevent it from spreading.

The primary goal is to evaluate and contrast the most effective algorithms for a web-based clinical decision support system applicable to the treatment of diphtheria. More specifically to: Evaluate the various web-based clinical decision support systems for diphtheria diagnosis and treatment and provide a comparison.

Use data analysis to categorise cases of diphtheria, and compare the efficacy of five popular classification methods (Naive base, K-nearest neighbour (KNN), Decision Tree (DT), Decision Stump (DS), and Rule Induction (RI)) on a suitable dataset in Rapidminer 6.2.

Despite the high levels of complexity and uncertainty in the sectors in which computers are utilised, intelligent systems have been created, including the use of fuzzy logic, artificial neural networks, and evolutionary algorithms (Jimoh et al., 2014).

2. DIPHTHERIA DISEASE AND EXPOSURE

In 1613, Spain experienced an epidemic of diphtheria, referred to as El Año de los Garrotillos (Hayes-Roth et al 1983). In 1705, the Mariana Islands experienced an epidemic of diphtheria and typhus simultaneously, reducing the population to about 5,000 people.

In 1735, a diphtheria epidemic swept through New England. Before 1826, diphtheria was known by different names across the world. In England, it was known as Boulogne sore throat, as it spread from France. In 1826, Pierre Bretonneau gave the disease the name diphthérite (from Greek διφθέρα, diphthera 'leather') describing the appearance of pseudomembrane in the throat.

In 1856, Victor Fourgeaud described an epidemic of diphtheria in California. In 1878, Princess Alice (Queen Victoria's second daughter) and her family became infected with diphtheria: Princess Alice and her four-year-old daughter Princess Marie both died.

In 1883, Edwin Klebs identified the bacterium causing diphtheria and named it Klebs–Loeffler bacterium. The club shape of this bacterium helped Edwin to differentiate it from other bacteria. Over the period of time, it was called Microsporon diphtheriticum, Bacillus diphtheriae, and Mycobacterium diphtheriae. Current nomenclature is Corynebacterium diphtheriae.

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Friedrich Loeffler was the first person to cultivate C. diphtheriae in 1884. He used Koch's postulates to prove association between C. diphtheriae and diphtheria. He also showed that the bacillus produces an exotoxin.

Joseph P. O'Dwyer introduced the O'Dwyer tube for laryngeal intubation in patients with an obstructed larynx in 1885. It soon replaced tracheostomy as the emergency diphtheric intubation method. In 1888, Emile Roux and Alexandre Yersin showed that a substance produced by C. diphtheriae caused symptoms of diphtheria in animals. In 1890, Shibasaburō Kitasato and Emil von Behring immunized guinea pigs with heat-treated diphtheria toxin. They also immunized goats and horses in the same way and showed that an "antitoxin" made from serum of immunized animals could cure the disease in non-immunized animals. Behring used this antitoxin (now known to consist of antibodies that neutralize the toxin produced by C. diphtheriae) for human trials in 1891, but they were unsuccessful. Successful treatment of human patients with horse-derived antitoxin began in 1894, after production and quantification of antitoxin had been optimized. Von Behring won the first Nobel Prize in medicine in 1901 for his work on diphtheria.

In 1895, H. K. Mulford Company of Philadelphia started production and testing of diphtheria antitoxin in the United States. Park and Biggs described the method for producing serum from horses for use in diphtheria treatment.

In 1897, Paul Ehrlich developed a standardized unit of measure for diphtheria antitoxin. This was the first ever standardization of a biological product, and played an important role in future developmental work on sera and vaccines. In 1901, 10 of 11 inoculated St. Louis children died from contaminated diphtheria antitoxin. The horse from which the antitoxin was derived died of tetanus. This incident, coupled with a tetanus outbreak in Camden, New Jersey, played an important part in initiating federal regulation of biologic products.

On 7 January 1904, Ruth Cleveland died of diphtheria at the age of 12 years in Princeton, New Jersey. Ruth was the eldest daughter of former President Grover Cleveland and the former first lady Frances Folsom.

In 1905, Franklin Royer, from Philadelphia's Municipal Hospital, published a paper urging timely treatment for diphtheria and adequate doses of antitoxin. In 1906, Clemens Pirquet and Béla Schick described serum sickness in children receiving large quantities of horse-derived antitoxin.

Between 1910 and 1911, Béla Schick developed the Schick test to detect pre-existing immunity to diphtheria in an exposed person. Only those who had not been exposed to diphtheria were vaccinated. A massive, five-year campaign was coordinated by Dr. Schick. As a part of the campaign, 85 million pieces of literature were distributed by the Metropolitan Life Insurance Company with an appeal to parents to "Save your child from diphtheria." A vaccine was developed in the next decade, and deaths began declining significantly in 1924.

In 1919, in Dallas, Texas, 10 children were killed and 60 others made seriously ill by toxic antitoxin which had passed the tests of the New York State Health Department. Mulford Company of Philadelphia (manufacturers) paid damages in every case.

In the 1920s, each year an estimated 100,000 to 200,000 diphtheria cases and 13,000 to 15,000 deaths occurred in the United States. Children represented a large majority of these cases and fatalities. One of the most infamous outbreaks of diphtheria occurred in 1925, in Nome, Alaska; the "Great Race of Mercy" to deliver diphtheria antitoxin is now celebrated by the Iditarod Trail Sled Dog Race.

In 1926, Alexander Thomas Glenny increased the effectiveness of diphtheria toxoid (a modified version of the toxin used for vaccination) by treating it with aluminum salts.[54] Vaccination with toxoid was not widely used until the early 1930s.[55] In 1939, Dr. Nora Wattie Principal Medical Officer (Maternity and Child Welfare) introduced immunization clinics across Glasgow, and promoted mother and child health education, resulting in the virtual eradication of the infection in the city.

Widespread vaccination pushed cases in the United States down from 4.4 per 100,000 inhabitants in 1932 to 2.0 in 1937. In Nazi Germany, where authorities preferred treatment and isolation over vaccination (until about 1939–1941), cases rose over the same period from 6.1 to 9.6 per 100,000 inhabitants.

Between June 1942 and February 1943, 714 cases of diphtheria were recorded at Sham Shui Po Barracks, resulting in 112 deaths because the Imperial Japanese Army did not release supplies of anti-diphtheria serum.

In 1943, diphtheria outbreaks accompanied war and disruption in Europe. The 1 million cases in Europe resulted in 50,000 deaths.

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In Kyoto during 1948, 68 of 606 children died after diphtheria immunization due to improper manufacture of aluminum phosphate toxoid.

In 1974, the World Health Organization included DPT vaccine in their Expanded Programme on Immunization for developing countries.

After the breakup of the former Soviet Union in 1991, vaccination rates in its constituent countries fell so low that an explosion of diphtheria cases occurred. In 1991, 2,000 cases of diphtheria occurred in the USSR. Between 1991 and 1998 as many as 200,000 cases in the Commonwealth of Independent States were reported, with 5,000 deaths. In 1994, the Russian Federation had 39,703 diphtheria cases. By contrast, in 1990, only 1,211 cases were reported.

In early May 2010, a case of diphtheria was diagnosed in Port-au-Prince, Haiti, after the devastating 2010 Haiti earthquake. The 15-year-old male patient died while workers searched for antitoxin.

In early June 2015, a case of diphtheria was diagnosed at Vall d'Hebron University Hospital in Barcelona, Spain. The six-year-old child who died of the illness had not been previously vaccinated due to parental opposition to vaccination. It was the first case of diphtheria in the country since 1986 as reported by "El Mundo" or from 1998, as reported by WHO.

In March 2016, a three-year-old girl died of diphtheria in the University Hospital of Antwerp, Belgium.

In June 2016, a three-year-old, five-year-old, and seven-year-old girl died of diphtheria in Kedah, Malacca, and Sabah, Malaysia.

In 2017, outbreaks occurred in a Rohingya refugee camp in Bangladesh, and in children unvaccinated due to the Yemeni Civil War.

In November and December 2017, an outbreak of diphtheria occurred in Indonesia with more than 600 cases found and 38 fatalities.

In November 2019, two cases of diphtheria occurred in the Lothian area of Scotland. Additionally, in November 2019 an unvaccinated 8-year-old boy died of diphtheria in Athens, Greece.

In July 2022, two cases of diphtheria occurred in northern New South Wales, Australia.

In October 2022 there was an outbreak of diphtheria at the former Manston airfield, a former MoD site in Kent, England, which had been converted to an asylum seeker processing centre. The capacity of the processing centre was 1,000 people, though about 3,000 were living at the site with some accommodated in tents. The Home Office, the government department responsible for asylum seekers, refused to confirm the number of cases.

3. PERFORMANCE ANALYSIS

3.1. Performance of the classification models

Table 3.1: Classification Process for Naïve Bayes Algorithm

Variable	Nominal Cross Validation (%)
Correctly classified instances	60.50
Incorrect classified instances	42.85
Correctly classified instances mikro	19.03
Kappa Statistics	0.064
Kappa Statistics mikro	0.060

$$y = \beta + R_1x_1 + B_1x_2 + \beta_3x_3 + B_4x_4 \quad (3.1)$$

$$y = 60.50 + B_1 42.85 + B_1 19.03 + \beta_3 0.064 + B_4 0.060 \quad (3.2)$$

The performance of the Naïve Bayes Classifier model using nominal cross validation shows that 60.50% of the instances in the dataset were correctly classified while 42.85% were incorrectly classified. The Kappa statistics reveal that the classification of this model is 0.064% reliable with a Kappa statistics mikro of 0.060% and 19.03% for the correctly classified mikro.

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3.2. Performance of K-nearest neighbor (K-NN)

Table: 3.2: Classification Process for K-nearest Neigbor Algorithm using the Rapidminer 6.2 Software

Variable	Nominal Cross Validation (%)
Correctly classified instances	41.00
Incorrect classified instances	19.81
Correctly classified instances mikro	13.00
Kappa Statistics	0.013
Kappa Statistics mikro	0.010

$$y = 41.00 + B_1 19.81 + B_1 13.00 + \beta_3 0.013 + B_4 0.010 \quad (3.3)$$

The performance of K-Nearest Neighbor model using nominal cross validation shows that 41.00% of the instances in the dataset were correctly classified while 19.81% were incorrectly classified. The Kappa statistics reveal that the classification of this model is 0.013% reliable with a Kappa statistics mikro of 0.010 and 13.00 for the correctly classified mikro.

Table 3.3: Classification Process for Decision Tree Algorithm using the Rapidminer 6.2 Software

Variable	Nominal Cross Validation (%)
Correctly classified instances	36.50
Incorrect classified instances	22.50
Correctly classified instances mikro	11.41
Kappa Statistics	0.122
Kappa Statistics mikro	0.008

$$y = 36.50 + B_1 22.50 + B_1 11.41 + \beta_3 0.122 + B_4 0.008 \quad (3.4)$$

The performance of Decision Tree model using nominal cross validation shows that 36.50% of the instances in the dataset were correctly classified while 22.50% were incorrectly classified. The Kappa statistics reveal that the classification of this model is 0.122% reliable with a Kappa statistics mikro of 0.008 and 11.41 for the correctly classified mikro.

Table 3.4: Classification Process for Decision Stump Algorithm using the Rapidminer 6.2 Software

Variable	Nominal Cross Validation (%)
Correctly classified instances	41.00
Incorrect classified instances	39.12
Correctly classified instances mikro	13.00
Kappa Statistics	0.066
Kappa Statistics mikro	0.006

$$y = 41.00 + B_1 39.12 + B_1 13.00 + \beta_3 0.066 + B_4 0.006 \quad (3.5)$$

The performance of Decision Stump model using nominal cross validation shows that 41.00% of the instances in the dataset were correctly classified while 39.12% were incorrectly classified. The Kappa statistics reveal that the classification of this model is 0.066% reliable with a Kappa statistics mikro of 0.006 and 13.00 for the correctly classified mikro.

3.3. Performance of Rule Induction

Table 3.5: Classification Process for Rule Induction Algorithm using the Rapidminer 6.2 Software

Variable	Nominal Cross Validation (%)
Correctly classified instances	52.50
Incorrect classified instances	38.34
Correctly classified instances mikro	28.04
Kappa Statistics	0.067
Kappa Statistics mikro	0.006

$$y = 52.50 + B_1 38.34 + B_1 28.04 + \beta_3 0.067 + B_4 0.006 \quad (3.6)$$

The performance of Rule Induction model using nominal cross validation shows that 52.50% of the instances in the dataset were correctly classified while 38.34% were incorrectly classified. The Kappa statistics reveal that the classification of this model is 0.067% reliable with a Kappa statistics mikro of 0.006 and 28.04 for the correctly classified mikro.

Table 3.6: Comparison of Classification Models Based on Accuracy

	Naïve Bayes (NB)	K-Nearest Neighbor (lazy.Ibk)	Decision Tree (DT)	Decision Stump (DS)	Rule Induction (RI)
Nominal X-Validation	60.50	41.00	36.50	41.00	52.50

4. CONCLUSION

This study carried out a web-based clinical decision support system to aid in the treatment of diphtheria, so that those who suffer from it can lead more fulfilling lives despite the disease. The outcome of both x- cross validation method is similar for all the classifiers. Naïve Bayes outperformed all other classifiers with accuracy being 60.50%. k-nearest neighbor, Decision Tree, Decision Stump and Rule induction perform well with the lowest accuracy for x- cross validation being 36.50%. Decision Tree falls behind in accuracy, while k-nearest neighbour and Decision Stump maintain accuracy at equilibrium 41.00%.

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