

A Bayesian Model and Bayesian Classification on the Data Obtained from Children's Educational Activity in the IoT Environment

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ARTICLE INFO	ABSTRACT
<p>Article History: Received 17 April 2023 Received in revised form 20 June 2023 Accepted 11 August 2023 Available online 22 August 2023</p>	<p>Over the past decade, there has been a significant increase in interest and research concerning the integration of technology within educational environments. A notable outcome of incorporating such technology in early childhood education is the enhancement of children's motivation, self-confidence, and collaborative abilities. The importance of early childhood education can be examined from two perspectives: the adaptability of young minds in contemporary times and the lasting impact of education during this formative period. To assess the effectiveness of technology in education, a study utilized Bayesian modeling to analyze data collected through Internet of Things (IoT) technologies. Specifically, a classifier was developed to predict future educational outcomes for children based on their previous performance. The test data confirmed the model's high accuracy, underscoring the positive potential of technology in shaping the educational experiences of young learners. This approach aligns with broader research trends that employ Bayesian networks to predict student performance and learning behaviors. For instance, studies have demonstrated the application of Bayesian models in forecasting student outcomes and identifying at-risk students, thereby facilitating timely interventions and personalized learning strategies. Such methodologies highlight the transformative role of technology and advanced analytics in modern education, particularly in enhancing early childhood learning experiences.</p>
<p>Keywords: Bayesian model, Bayesian classification, Education, Internet of Things</p>	

1. INTRODUCTION

One of the fundamental aspects of human existence is education. Education involves a series of deliberate decisions and actions that aim to help students achieve specific objectives. Teaching is an activity that an instructor plans to promote learning and occurs through interactions between the teacher and one or more students. In essence, teaching encompasses any pre-planned activity or strategy intended to facilitate learning [1]. Studies have demonstrated that the lack of appropriate training and activities during childhood may result in reduced effectiveness of those same activities in fostering child development later on. Childhood education is essential from two

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perspectives: the ease of influencing children at this stage in development, and the durability of the long-term impact of learning during this period.

We live in a contemporary, technology-driven world where technology has a direct or indirect impact on every individual's daily life. Research has demonstrated that incorporating technology can boost children's learning. To effectively integrate technology into teaching and learning, it is essential to adhere to the following guidelines: maintain an objective approach, present data in a concise and logical manner, utilize conventional academic structures, use clear and unbiased language, follow proper formatting standards, employ a formal writing style, provide a coherent structure with clear causal connections, avoid biased language, utilize precise subject-specific vocabulary, and ensure grammatical accuracy.

The COVID-19 pandemic has brought about significant changes in the educational activities of children. Andrew et al. (2020) conducted a study to understand the impact of the COVID-19 lockdown on children's experiences of home learning in England [2]. The findings of the study highlighted the inequalities in children's experiences of home learning during the lockdown. With the shift towards remote learning, there is a growing need for innovative technologies to support educational activities in children's homes.

One such technology that has gained attention is the Internet of Things (IoT) environment. Manogaran et al. (2019) proposed a Wearable IoT Smart-Log Patch, which is an edge computing-based Bayesian deep learning network system for multi-access physical monitoring system [3]. This system could be adapted to monitor and support children's educational activities in the IoT environment. The use of Bayesian models and Bayesian classification in this context could provide valuable insights into the learning behaviors and preferences of children in home-based educational settings.

Verlenden et al. (2021) studied the association of children's mode of school instruction with child and parent experiences and well-being during the COVID-19 pandemic [4]. The findings of this study emphasized the need to understand the impact of different modes of instruction on children's educational activities and overall well-being. Integrating Bayesian models and classification techniques in analyzing the data obtained from children's educational activities in the IoT environment could provide a comprehensive understanding of the factors influencing children's learning experiences.

Moreover, Alhakami et al. (2019) proposed a nonparametric Bayesian approach for network anomaly intrusion detection [5]. While the focus of this study was on cybersecurity, the nonparametric Bayesian approach could be adapted to analyze the data obtained from children's educational activities in the IoT environment. By incorporating feature selection techniques, this approach could help in identifying patterns and anomalies in children's learning behaviors, thereby contributing to the development of effective learning support systems.

Niu et al. (2020) presented a multichannel deep attention neural network for the classification of autism spectrum disorder using neuroimaging and personal characteristic data [6]. Although the focus of this study was on autism spectrum disorder, the deep attention neural network could be utilized to analyze the data obtained from children's educational activities. This could aid in identifying specific learning characteristics and preferences of children in the IoT environment, thereby facilitating personalized educational interventions.

In addition, the study by Karem et al. (2019) highlighted the importance of evaluating the language abilities of multilingual preschoolers using the International Classification of Functioning, Disability and Health-Children and Youth Version [7]. By incorporating classification techniques based on the Bayesian model, it would be possible to develop a comprehensive framework for assessing and categorizing the educational activities and language learning experiences of multilingual preschoolers in the IoT environment.

Furthermore, the decision-making process in the IoT environment can be enhanced through unsupervised learning, as proposed by Piccialli et al. (2020) [8]. The application of unsupervised learning techniques in the context of children's educational activities could provide valuable insights into the learning patterns and behaviors of children in the IoT environment, thereby contributing to the development of adaptive and responsive educational systems. Finally, Love et al. (2019) conducted a cross-sectional analysis of socioeconomic and ethnic differences in children's vigorous intensity physical activity [9]. While the focus of this study was on physical activity, the findings underscored the influence of socioeconomic and ethnic factors on children's engagement in physical activities. Similarly, understanding the impact of these factors on children's educational activities in the IoT environment is crucial for developing inclusive and effective learning support systems.

In conclusion, the integration of Bayesian models and Bayesian classification techniques in analyzing the data obtained from children's educational activities in the IoT environment holds great potential for gaining insights into children's learning behaviors, preferences, and challenges. Future research in this area should focus on developing adaptive and personalized learning support systems that can cater to the diverse needs of children in home-based educational settings, particularly in the context of the ongoing changes in educational practices due to the COVID-19 pandemic.

2. RELATED WORKS

In this section, we will discuss the research on using IoT for data collection and management in the education of children. Uzelac et al. conducted a comprehensive study on parameters in the physical environment through IoT that affect students' concentration during lectures [10]. Their research analyzed the effect of various parameters of the classroom's physical environment on students' concentration. The primary objective of this study is to determine the key factors that significantly impact the ability of students to concentrate during lectures. Upon completing our analysis, we identified five parameters that significantly influence student concentration using IoT technology. To achieve this, a number of parameters were measured in a classroom setting utilizing affordable smart devices. Our research is based on data collected from 14 lectures attended by 197 students.

Pervez and colleagues examine the ways in which Internet of Things (IoT) technology supports teachers and students in the learning process [11]. The findings can inform administrators as they develop tailored educational models. This is achieved by analyzing large volumes of data from IoT devices. Wearable sensors can be placed on students' foreheads to provide teachers with important information about their unique learning styles, allowing for customized curricula to better meet their needs. Personalized learning enables teachers to meet the individual needs of their students by gathering feedback. Additionally, integrating social media platforms like Facebook and Twitter into students' accounts facilitates data collection by researchers who can then utilize it to create more captivating course content.

Njeru and colleagues analyze the utility of IoT in capturing and managing the large data sets generated by online courses for assessing and identifying common learning scenarios among students [12]. Historically, education relied on traditional classroom methods where teachers were compelled to gather data on student performance through observation, evaluation, and classroom activities. IoT aids in enhancing e-learning by lowering expenses and boosting learning outcomes. The collected and analyzed data assists teachers in obtaining a more profound understanding of the learning process while also providing feedback and guidance to pupils. This research endeavors to investigate how smart objects could enhance online course data gathering and use intelligent agents for analysis and feedback delivery, all while avoiding human intervention. The proposed solution employs three layers, as illustrated in Figure 1, to implement this approach efficiently.

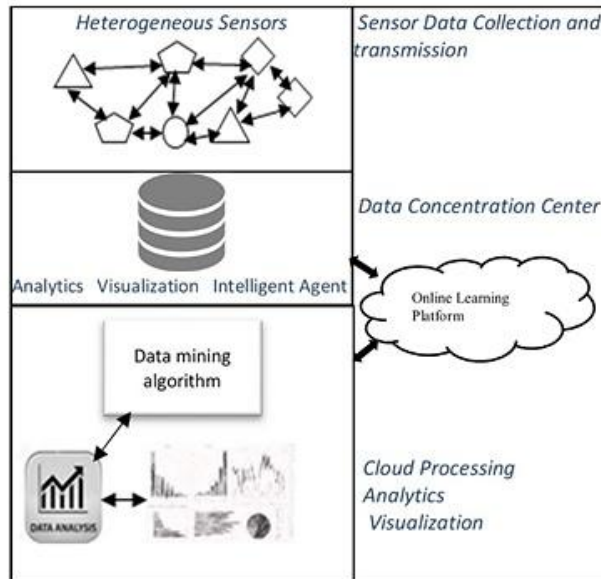


Fig. 1. Layers of the model proposed by Njeru et al. in the use of IoT in learning [12]

A network of diverse sensors will connect to the online learning platform. The sensors gather information, including data storage time stamps. The data then transfers to the database system using the HTTP protocol. Time series tags the data in the storage section of the database system for precision and integrity. Analyzing and organizing data in a database creates a seamless flow of information. An algorithm is designed to analyze the database and generate reports to facilitate informed decision-making regarding ways to enhance learning. In addition, learners receive feedback.

Vharkute and Wagh explored IoT architecture in electronic learning [13]. Data mining tools employ data gathered from IoT sensors to assess student performance. The Apriori algorithm has been employed to assess students' results by examining the interdependence between their communication skills, work ethic, abilities, logical thinking, verbal aptitude, and others. For instance, a student with strong logical thinking may also exhibit a high level of work ethic. The C4.5 (Decision Tree Algorithm) is utilized to analyze the findings, determining how many students can pass the exam based on their communication skills and ability. It is advantageous to present findings visually.

Rahman and Bhuiyan devised and developed a prototype platform for analyzing signals concerning children with special needs, to comprehend their circumstances and challenges, and enact interventions to enhance students' learning efficacy [14]. The proposed model stores students' information through wearable devices and sensors for processing aimed at machine learning, analysis, and deeper understanding. The sensors collect data sent to a central repository for collaborative study that promotes further investigation. The objective is to discover a suitable model, whether through a human-guided fuzzy logic model or an expert system, neural network, and decision tree. Special high-level data operations, such as machine learning and analytics, are conducted on the data collected by sensors. Clear and concise statements are provided with logical connections between them. Technical terms are explained, and quotes are clearly marked. The language is formal, balanced, and objective, avoiding colloquialism, filler words, ambiguity, and ornamental language. Consistent footnotes, citations, and formatting features are employed, adhering to style guides. The spelling and grammar meet the requirements of American English.

3. PROPOSED METHOD

In this section, the proposed educational method has been presented. Figure 2 shows the diagram of the proposed educational method. The proposed method consists of several levels, each of which has its own input and output. For each level, the tools specified in the figure are used. As seen in Figure 2, the tools used in each level of the

proposed teaching method are described. IoT, Internet of Things, CN, complex network, BM, Bayesian model, MADM, multiple attributes decision making and SDI, selective dissemination of information. The focus of this research is on analyzing the data obtained from the IoT and creating a Bayesian model.

Teachers communicate with children's parents through the Internet and provide educational materials to parents. Also, teachers communicate with each other through the Internet and discuss educational materials. Parents teach educational content to their children. Parents can also communicate with each other and discuss educational matters. Children communicate with each other through WISP/NFC and teach each other educational materials according to the protocol in Figure 3. Also, Figure 4 shows the complex network of communication between teachers, parents and children. Children are marked with circle shape and blue color, parents with triangle shape and red color, and teachers with square shape and green color.

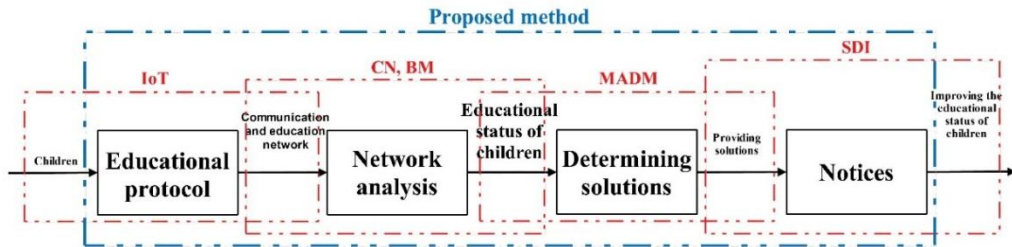


Fig. 2. Diagram of the proposed educational method and its constituent levels

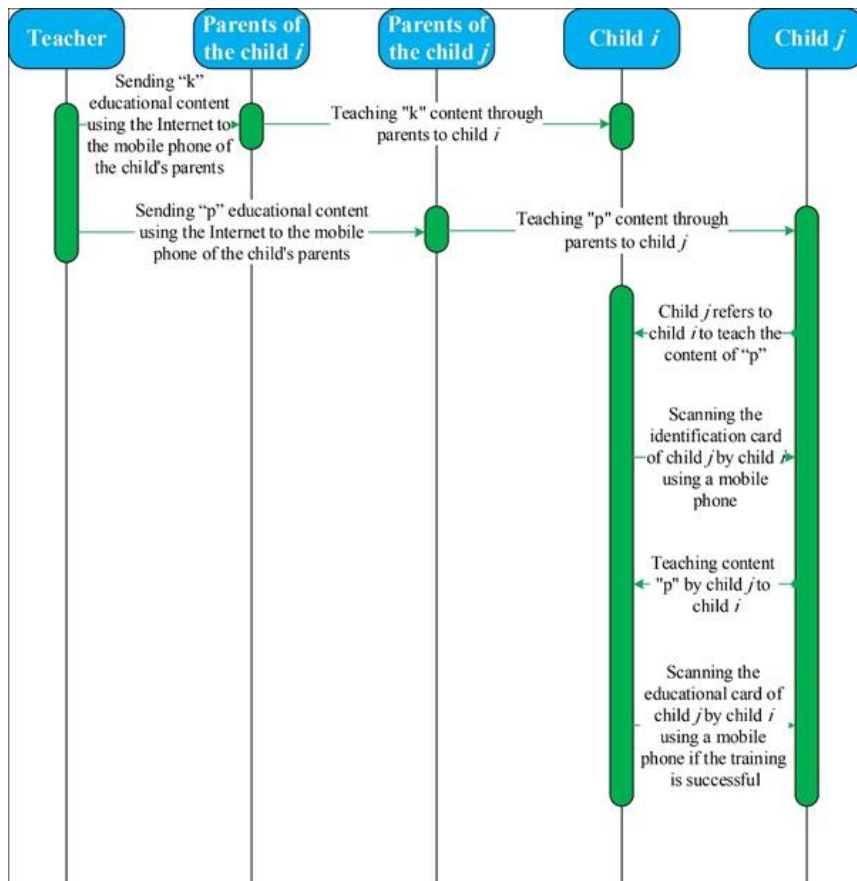


Fig. 3. Content exchange and interaction protocol

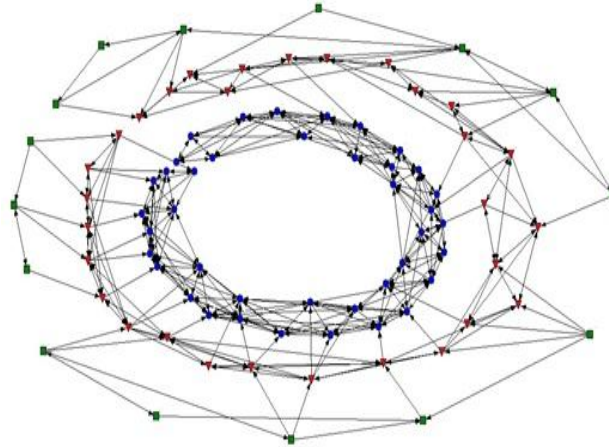


Fig. 4. Complex network of teachers, parents and children

After collecting data from the Internet of Things during the education process, it can be modeled using Bayesian methods to calculate conditional probabilities. Additionally, a Bayesian classification can be developed using training and test data obtained from the proposed training method to estimate a child's label based on their previous records. Bayesian networks are among the methods used for uncertainty control in problems based on probability theory. In many intelligent systems, requests for event probability based on observations must be answered objectively. Calculating the conditional probability of an event, given certain observations, is often desirable. This can be done using the conditional probability formula and the sum of elements from their distribution table. Technical term abbreviations will be explained when first used. The writing will be in passive tone with correct avoidance of biased, emotional, figurative, ornamental, colloquial, and informal language. Filler words will be avoided, and specific vocabulary will be used when applicable. Citations will be consistent with formal language, and grammatical errors, spelling mistakes, and punctuation errors will be avoided. Equation (1) describes the probability of event x , given that y exists.

$$P(x|y) = \frac{P(x \wedge y)}{P(y)} \quad (1)$$

Assuming dependence in the form of directed graphs with no rounds leads to the development of a distribution model, known as Bayesian networks. This directed graph contains vertices that provide information on conditional probability values. These variables can be either discrete or continuous, and the network includes various components and features.

1. A set of random variables constitutes the graph's vertices, which may be either discrete or continuous.
2. A set of directed edges, if an edge is from vertex X to vertex Y , we call X the parent of Y .
3. Each node X_i has a conditional probability distribution $P(X_i|Parents(X_i))$ which numerically shows the influence of parent nodes on this node.
4. The graph has no directed cycles and, in reality, is a directed acyclic graph.

Using Bayes theory, the probability of a sample's class label can be estimated. The characteristic attribute of a class, C , with m distinct values in the training data set D is used to estimate the label of a sample like d . To calculate the label of d , calculate all conditional probabilities $P(C=c_i|d)$ and choose the one with the highest probability. If the data set D has n attributes, d can be expressed as Equation (2).

$$d = \langle A_1=a_1, A_2=a_2, \dots, A_n=a_n \rangle \quad (2)$$

Based on this, Bayes' law can be shown as Equation (3).

$$\frac{P(C=c_i | A_1=a_1, \dots, A_n=a_n) = P(A_1=a_1, \dots, A_n=a_n | C=c_i) \times P(C=c_i)}{P(A_1=a_1, \dots, A_n=a_n)} \tag{3}$$

Equation (3) calculates the probability of class labels and selects the label with the highest probability. To estimate the class label, only calculate Equation (3) and skip computing the probability value $P(A_1 = a_1, \dots, A_n = a_n)$, which is the same for all classes and does not affect the decision-making process [15].

4. SIMULATION

The educational protocol shown in Figure 3 was implemented in two language kindergartens. In the following, the distribution of data and creation of Bayesian network and Bayesian classification are described.

4.1. Data Distribution

In this section, the distribution of data obtained from the IoT in the education process has been investigated. Given that each child can be a good or poor learner, a good or poor educator, it follows the Bernoulli distribution. A random experiment with only two values is a Bernoulli trials. The results of the Bernoulli trials are usually marked as "success" or "failure". If X is a random variable that takes success with probability p and failure with probability 1-p, then X is called a random variable with Bernoulli distribution. P is called the Bernoulli distribution parameter, which is a value between zero and one. In order to represent the Bernoulli distribution for the random variable X, $X \sim B(1, p)$ is used. The sum of n Bernoulli random variables with the same parameter has a binomial distribution, and if X is such a random variable, it is displayed as $X \sim B(n, p)$. The probability of obtaining k success is determined by the probability mass function of Equation (4).

$$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k} \tag{4}$$

According to formula 4, the distribution of data resulting from the implementation of the training process for success or learning and failure or lack of learning is equal to Equation (5).

$$P(X=k) = \binom{n}{k} 0.89^k 0.11^{n-k} \tag{5}$$

Also, the distribution of the data obtained from the implementation of the training process, for success equal to a strong educator and failure equal to a weak educator, is equal to Equation (6).

$$P(X=k) = \binom{n}{k} 0.78^k 0.22^{n-k} \tag{6}$$

4.2. Modeling Using Conditional Probability Model

The previous section covered data distribution. This section will explore Bayesian modeling as a means to calculate joint and conditional probability distributions. Figure 5 illustrates the conditional probability model for the educational status of children. Experiment 1 is the pre-solution data while Experiment 2 is the post-solution data. Using the conditional probability model presented in Figure 5, we can determine the probability of a child's future educational status based on their previous status. Additionally, we can calculate the probability of students' educational status after interventions, based on their status prior to the interventions. For instance, we can compute the likelihood of a child being a poor learner before interventions, given their low input communication and high output communication. It is important to note that technical term abbreviations will be explained when initially used.

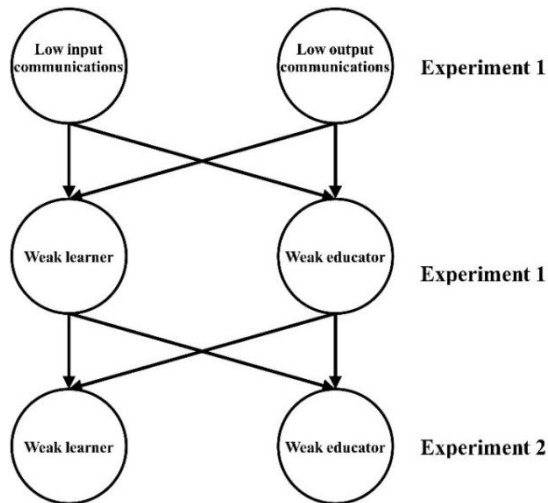


Fig. 5. Conditional probability model of educational status of children

MATLAB software was utilized to implement a conditional probability model of the educational status of children. The probabilities were calculated using data from communication and education networks obtained during the language kindergarten education process. Figure 6 displays the MATLAB code for the studied conditional probability model.

```

5
6 %% A %%
7 for j=1:n
8     sum=0;
9     for i=1:n
10        sum=sum+CN1(i,j);
11    end
12    if sum<=(n/2)
13        A(j,1)=1;
14    else
15        A(j,1)=0;
16    end
17 end
18
19 sum=0;
20 for i=1:n
21    sum=sum+A(i,1);
22 end
23 PA(1,1)=(sum/n);
24 PA(2,1)=(1-PA(1,1));
25
26 %% B %%
27 for i=1:n
28    sum=0;
29    for j=1:n
30        sum=sum+CN1(i,j);
31    end
32    if sum<=(n/2)
33        B(i,1)=1;
34    else
35        B(i,1)=0;
36    end
37 end
38
39 sum=0;
40 for i=1:n

```

Fig. 6. A view of the MATLAB code in the implementation of the conditional probability model of children's educational status

In this implementation, communication and training networks are received as input. Then the conditional probabilities are calculated based on the conditional probability model. Figure 7 shows the probabilities of each status in the implementation of the studied conditional probability model.

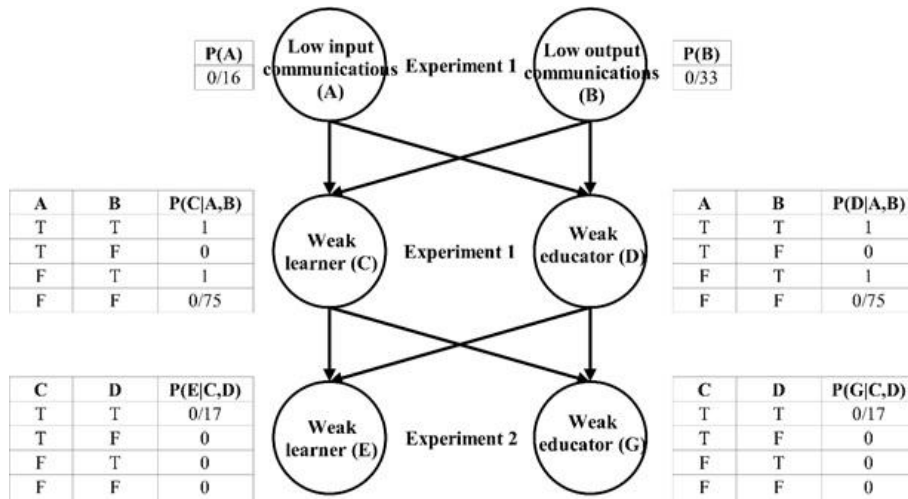


Fig. 7. The probabilities obtained in the implementation of the conditional probability model of children's status

As can be seen in the conditional probability model of Figure 7, the probability that a child will be a poor learner or a weak educator after providing the solutions in the proposed method is 0.17, provided that he be weak learner and weak educator before the solutions.

4.3. Classification with the Help of Bayes Rule

In this section, the creation of Bayesian classification for educational data resulting from the implementation of the proposed method in the second language kindergarten is discussed. Table 1 shows the training data.

Table 1. Educational data collection resulting from the implementation of the proposed method in the second language kindergarten

ID	IC	OC	IE	OE	Class
1	w	w	w	w	g
2	g	w	w	w	g
3	g	g	w	w	g
4	g	g	w	w	w
5	g	g	w	w	g
6	g	g	g	g	g

IC attribute shows children's input communication status, OC, children's output communication status, IE, learning status, and OE shows children's teaching status in the first test and before providing solutions. Class shows the learning status of children in the second test and after providing solutions. g expresses a good status and w expresses a poor status. In the following, conditional probabilities are calculated to create Bayesian classification.

$$P(Class=g) = 0.83$$

$$P(IC=g|Class=g) = 0.8$$

$$P(IC=g|Class=w) = 1$$

$$P(OC=g|Class=g) = 0.6$$

$$P(OC=g|Class=w) = 1$$

$$P(IE=g|Class=g) = 0.2$$

$$P(IE=g|Class=w) = 0$$

$$P(OE=g|Class=g) = 0.2$$

$$P(OE=g|Class=w) = 0$$

$$P(Class=w) = 0.17$$

$$P(IC=w|Class=g) = 0.2$$

$$P(IC=w|Class=w) = 0$$

$$P(OC=w|Class=g) = 0.4$$

$$P(OC=w|Class=w) = 0$$

$$P(IE=w|Class=g) = 0.8$$

$$P(IE=w|Class=w) = 1$$

$$P(OE=w|Class=g) = 0.8$$

$$P(OE=w|Class=w) = 1$$

In the following, the evaluation of the classifier using the data obtained from the implementation of the proposed method in the first language kindergarten as test data has been discussed. Table 2 shows the test data.

Table 2. Test data obtained from the implementation of the proposed method in the first language kindergarten

ID	IC	OC	IE	OE	Real Class
1	g	g	w	g	g
2	g	w	g	w	g
3	g	g	g	g	g

To estimate the class label of sample 1:

$$P(\text{Class}=g) \times \prod_{j=1}^4 P(A_j = a_j | \text{Class}=g) = 0/83 \times 0/8 \times 0/6 \times 0/8 \times 0/2 = 0/06$$

$$P(\text{Class}=w) \times \prod_{j=1}^4 P(A_j = a_j | \text{Class}=w) = 0/17 \times 0/99 \times 0/99 \times 0/99 \times 0/01 = 0/001$$

Therefore, the estimated label for sample 1 is equal to class g. To estimate the class label of sample 2:

$$P(\text{Class}=g) \times \prod_{j=1}^4 P(A_j = a_j | \text{Class}=g) = 0/83 \times 0/8 \times 0/4 \times 0/2 \times 0/8 = 0/04$$

$$P(\text{Class}=w) \times \prod_{j=1}^4 P(A_j = a_j | \text{Class}=w) = 0/17 \times 0/99 \times 0/01 \times 0/01 \times 0/99 = 0/00001$$

Therefore, the estimated label for sample 2 is equal to class g. To estimate the class label of sample 3:

$$P(\text{Class}=g) \times \prod_{j=1}^4 P(A_j = a_j | \text{Class}=g) = 0/83 \times 0/8 \times 0/6 \times 0/2 \times 0/2 = 0/01$$

$$P(\text{Class}=w) \times \prod_{j=1}^4 P(A_j = a_j | \text{Class}=w) = 0/17 \times 0/99 \times 0/99 \times 0/01 \times 0/2 = 0/0003$$

Therefore, the estimated label for sample 3 is equal to class g. As seen in Table 2, the classifier correctly estimated the class label of the test data. Also, by using Bayesian classifications, it is possible to see the probability of each sample belonging to the assigned class.

5. CONCLUSION

This study employed Bayesian modeling and classification techniques, leveraging data obtained through the implementation of the Internet of Things (IoT) in the realm of education. The Bayesian model, with its capacity to consider conditional probabilities, facilitated the calculation of a child's likelihood of educational progression based on their prior status. The dataset underwent division into two distinct groups: training and testing data. This division was instrumental in the creation of categories through Bayesian classification.

Following the construction of the classifier using the training dataset, the accuracy of the classification generated was evaluated using the test dataset. The repetition of this process with both datasets underscored the robustness of the classifier. The study's findings prominently showcased the high precision achieved through the classification, emphasizing the efficacy of Bayesian modeling and classification in predicting educational outcomes based on IoT-collected data.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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