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CPU and eGPU Support System Based on Naive Bayes Classification

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Abstrak

Central Processing Unit (CPU) dan External Graphics Processing Unit (eGPU) dikenal sebagai overclocks yang bertujuan agar perangkat melebihi benchmark yang ditetapkan oleh pembuat perangkat. Namun hingga saat ini belum ada penentuan untuk merangking kedua hardware tersebut dalam batasan tertentu seperti kisaran harga hardware dari tahun ke tahun. Simple Additive Weighting (SAW) digunakan untuk mentukan peringkat hardware setiap tahunnya pada CPU berdasarkan nilai Cores, Threads, Base, Clock, dan TDP serta eGPU berdasarkan nilai Memory, Bit Rate, GPU Clock, dan Memory Clock kemudian pada kedua hardware tersebut dikelompokkan berdasarkan harga. Fokus penelitian ini untuk menguji algoritma klasifikasi Naïve Bayes dalam untuk menentukan hasil kombinasi kriteria antara kedua perangkat keras tersebut untuk menentukan kriteria yang memungkinkan menjadi "tidak baik" dan "baik". Klasifikasi ini digunakan untuk menentukan kriteria probabilitas pemilihan kombinasi perangkat keras CPU dan eGPU. Pengujian yang dilakukan pada penerapan Naïve Bayes menggunakan 80% data latih yang memiliki 2776 data dan 20% data uji yang memiliki 695 data yang akan diuji akurasi, presisi, recall, dan F1-score. Untuk hasil pengujian yang telah dilakukan mendapatkan hasil akurasi 0,78, presisi 1, Recall 0,764, dan F1-Score 0,866.

Kata kunci*— Simple Additive Weighting, Naïve Bayes, Klasifikasi*

Abstract

Central Processing Unit (CPU) and External Graphics Processing Unit (eGPU) known as overclocks which aim to make device exceed the benchmarks set by the device maker. However, until now there has been no determination to rank the two hardware within certain limits, such as the hardware price range. Simple Additive Weighting (SAW) is used to determine CPU rank based on values of Cores, Threads, Base, Clock, and TDP and eGPU based on values of Memory, Bit Rate, GPU Clock, and Memory Clock then on both hardware are grouped based on price. Focus of this research is to test Naïve Bayes classification algorithm to determine results of the criteria combination between two devices to determine the possible criteria to be "bad" and "good". This classification is used to determine the probability criteria for selecting the combination of CPU and eGPU hardware. Tests carried out on the application of Naïve Bayes use 80% of training data which has 2776 data and 20% of test data which has 695 data to be tested for accuracy, precision, recall, and F1-score. The results of the tests that have been carried out, the results obtained an accuracy of 0.78, precision 1, Recall 0.764, and F1-Score 0.866.

Keywords— *Simple Additive Weighting, Naïve Bayes, Classification*

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1. INTRODUCTION

The needs of computer users are often hampered by the limitation of hardware scores set by the manufacturer of the hardware, which results in a less satisfying user experience when using the product. The results of performance improvements that exceed the limits set by the hardware manufacturer from the overclock process, much has been done by other users and often shared on a website that displays the highest score from the CPU and eGPU. But there is no specific ranking on the hardware that has known the score. Therefore it is necessary to rank to determine the weight value per hardware to find out which is the best in its class. Classification needs to be done to determine the criteria for hardware combination from the learning process of data that has been processed so that if there is input of a hardware combination that has never been combined, the probability of the criteria to know whether the hardware combination is good or not good.

Overclocking the processor can reduce the execution time of using the program, or in other words can optimize the performance of the processor. In research [1] examines about improving processor performance through overclocking components by controlling the power consumption of existing power. According to [2] the limitation in increasing the clock rate when overclocking is about temperature and resources, but resources can be overcome by choosing the type of PSU that suits the needs used according to the hardware or other components used, to overcome the temperature can use better pasta thermal or liquid metal.

In the research [3] explained that the innovation of the GPU card technology company is always inspired by its own consumers in various ways to find out the desires of consumers about products that have been previously marketed, such as user feedback about product expectations that are not as expected by these users, thus developing the idea of GPU card technology product concepts such as NVIDIA and AMD Radeon always continue to upgrade their latest GPU technology to the Overclock series to be able to get a higher boost memory clock.

Research on the effect of overclocking the eGPU [4] which utilizes the CPU and eGPU to measure the performance of hashcat usage with Nvidia GeForce GTX 1060 with a default clock of 1680 MHz produces a benchmark of 10112.8 MH / s while when overclocked with the Clock 1946 MHz resulted in a benchmark of 11153.2 MH / s which resulted in a higher difference of 1040.4 MH / s. Other eGPU uses were also discussed [5] on their use for the case of Bitcoin mining activities reviewed on the eGPU under the Nvidia Corporation brand and Advanced Micro Devices, Inc which have underclocked and overclocked variants.

According to [6] text mining is used to obtain existing information from mining in text grouping, to determine sentiment analysis or as a summarizing of documents from the results of data taken and also in the study data from text mining is cleaned before being processed to get better results.

The Simple Additive Weighting (SAW) method is one of the methods in decision support systems [7] describing that method has the basic concept of using Simple Additive Weighing by finding the weighted sum of the rankings of each alternative on all attributes. According to [8] solving the selection problem in multi-process decision making which has many attributes is recommended to be solved using the Simple Additive Weighting (SAW) method.

Using SAW [9], as ranking in attribute the Weights of success factors e-Government strategies proposed by Turkey's ministries, explained by [10] the SAW method in decision support systems can display the ranking of prospective assemblies as a pastor's consideration to determine the decision making process taken with determine the making of criteria to be given weight, benchmarks can be made for someone who makes a decision.

Selection of eGPU with SAW [11] creates a mobile application to search for eGPU selections by entering the variables of price limits, user requirements, processing speed, and memory size. Decision support systems that are made are based on user characteristics and there is no ranking between eGPUs for Memory, Bit Rate, GPU Clock, or Memory Clock values.

Research on Overclock, the use of the Simple Additive Weighting (SAW) Method to rank and Naïve Bayes to make predictions has been done, therefore the authors review similar studies, the research is as follows:

Overclock research has been investigated by [12] There are many guidelines on how to overclock a computer CPU, the research takes one way from Xbitlabs and modifies it. In research shows the effects of CPU overclocking to Genetic Algorithms. For the CPU, using the Intel core 2 duo E6420, the original frequency is 2.13 GHz, and has managed to reach 3.20 GHz or about 50% increase. For the genetic part using the Rastrigin function, the number of generations is set to 5,000 generations and in both cases. After the overclocking process get a 20% performance increase.

In ranking using the Simple Additive Weighting Method (SAW) conducted in research [13] with the aim of determining the Principal in Experimental School, with SAW can choose the best alternative from several alternatives using each predetermined criteria including written test, social competence, portfolio, best practice, video, interview, exemplary, and presentation. In the defined criteria, weights are made and then a ranking is made, from 7 candidate school principals' data it is determined that an alternative data named Selamat Riadi, S.Pd gets first rank with 7.67 out of 8 predetermined criteria.

Predictions using the Naïve Bayes algorithm were investigated by [14]researching about systematic analysis of various types of features to characterize medicine pairs. These features include information about medicine targets, proteins, side effects, metabolic enzymes, and medicine transporters. Next Naïve Bayes algorithm is used to build a classification model to predict effective medicine combinations using each of the types of features that have been defined. The results show that features based on medicine targets produce the best performance, reflecting that protein is often used in a combination of medicine data sets. The clinical side effect feature is well done, based on the assumption that medicine partners can often not have the same or similar adverse medicine reactions. Novel features of enzyme-based information show better performance than conventional features, suggesting an important role of the metabolic enzymes of medicines in the prediction of medicine combinations.

Comparison of classification using the Naïve Bayes and K-NN algorithms [15] for the purpose of classifying volcanic activity based on 5 criteria for shallow volcanic earthquakes, distant tectonic earthquakes, deep volcanic earthquakes, gusts of earthquake and mountain status. The test results of this study on the 3 k-fold test resulted in the Naïve Bayes algorithm having an accuracy of 79.71% with a standard deviation of 3.55% while the K-NN algorithm had an accuracy of 63.68% with a standard deviation of 7.47%.

In a research discussion [16] using the Naïve Bayes algorithm in machine learning based on data training, using conditional probabilities as a requirement and also from the classification results obtained can classifier the possibility of new data that will be in the membership of a class. [17] examined using the Naïve Bayes algorithm to classifier based on classifications from one classification then from data that has been trained or the results of classifications combined and made a final decision based on the results of the sum of the classification models.

Research comparing the Naïve Bayes algorithm and C4.5 in the classification of data mining [18] both algorithms are very effective in accepting “Kartu Indonesia Sehat”. For determining the age of birth, the Naïve Bayes algorithm is the best, while in determining the credit card application at the bank, the C4.5 algorithm is the best.

The use of the SAW method is used in this study to determine the CPU data ranking based on the values of Cores, Threads, Base, Clock, and TDP on the hardware as well as eGPU ranking based on the values of Memory, Bit Rate, GPU Clock, and Memory Clock. The application of the Naive Bayes classification algorithm is used to determine the criteria for the combination of CPU and eGPU data into the "Good" and "Not Good" classifications. The focus of this research is to test the Naive Bayes classification algorithm in determining the classification of the CPU and eGPU data calculations which have been ranked based on the best value with the SAW method of each alternative that has been ranked based on the criteria value for each alternative and which has been grouped based on the price of a cheap, medium, and expensive.

2. METHODS

2.1 Data Collection

We collect central processing unit (CPU) data with AMD and Intel brands using text mining from CPUPB Techpowerup data for a period of 3 years and the data has attributes including name, brand, codename, cores, clock, socket, process, L3 cache , TDP, and released. Next we collect data based on the single core score and multi core score attributes of the Geekbench Processor Benchmark based on the CPU name obtained from techpowerup and to complete the data obtained so that it has a price for each CPU hardware, we collect price data from Amazon. In total AMD CPU data totaled 35 in 2017, 25 in 2018, 11 in 2019 and Intel CPU data amounted to 44 in 2017, 44 in 2018, 31 in 2019.

Next we collected data from external graphics processing units (eGPU) from Techpowerup GPU-Specs with the same time span of 3 years, from text mining that was carried out having product name attributes, GPU Chip, Released, Bus, Memory / DDR / Bitrate, GPU Clock , Shaders / TMUs / ROPs. To complete the 3D Mark Score, we collect data from the Geekbench Opencl Benchmark to get detailed data on the 3D Mark Fire Strike Graphics Score attribute, and then the price data is taken from Amazon. The results of the data obtained in text mining on AMD brand eGPU are 56 data in 2017, 49 data in 2018, 37 data in 2019. While in eGPU with the NVIDIA brand are 38 data in 2017, 39 data in 2018, 41 data in 2019.

2.2 Simple Additive Weighting (SAW) Method

SAW method is one method that is often used for decision making where the aim is to find the best performance rating for each alternative on all attributes. The SAW method uses the decision matrix normalization process (x) which is compared with all available alternative rankings. In the SAW method there are 2 attributes, namely cost (Min) and benefit (Max). The steps for solution are [19]: Determining the alternatives, Determining the criteria, Providing the match rating value of each alternative on each criterion, Determining the preference weight or level of importance (W) of each criterion, Making a match rating table of each alternative on each criterion, Making a decision matrix (X), Normalizing the decision matrix, Normalized performance rating, Preference weight, a larger result indicates the best alternative.

2.3 Naïve Bayes

Naïve Bayes is a probabilistic classifier based on the Bayes theorem, [20] Classifiers using Naïve Bayes assume that the effect of variable values on a given class does not depend on the values of other variables, this assumption is called the conditional independence class. In Bayes' Theorem Probility (B given A) = Probility (A and B) / Probility (A) which means to calculate the probability of B given A, the algorithm counts the number of cases where A and B occur together and divides it by the number of cases where A occurs self. Bayes's classification is based on the Bayes theorem, taken from the name of a mathematician who is also the minister of the British Prebysterian, Thomas Bayes (1702-1761), [21].

Naïve Bayes classifiers based on the Bayes theorem are applying probabilistic statistical classifications, where the meaning of the word "naïve" indicates that there is conditional independence between features or attributes. The main advantage is simpler than other classification algorithms that can handle datasets with a large number of attributes. Naïve Bayesian classifier has the following [22]: (1) Training set and class labels. (2) The Naïve Bayesian classifier the tuple X including the Ci. (3) If the prior probability class is not known, then it is assumed that each class has the same prior probability. (4) ie the values of the attribute are conditionally independent between one attribute with another attribute, if given the class label of the tuple. So:

$$\boldsymbol{P(H|X)} = \frac{P(X|H)P(H)}{P(X)} \tag{1}$$

2.4 Testing

For testing will use Precision, Recall, F1-Score, and Accuracy. Precision is the number of true positive classifications compared to the total positive classifications. Recall is the number of true positives compared to all positive data. F1-Score is a comparison of average precision and recall given weight. Accuracy is the number of positive and negative true classifications with the total data [23].

$$Precision = \frac{TP}{TP+FP}\ x\ 100\% \tag{2}$$

$$Recall = \frac{TP}{TP+FN}\ x\ 100\% \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\% \tag{4}$$

3. RESULTS AND DISCUSSION

With the application of text mining to obtain CPU and eGPU data, then the data is normalized and then stored in a database. After that the application of the SAW method is applied to obtain hardware ranking in accordance with predetermined criteria, the results of the SAW ranking are processed again on the Naïve Bayes algorithm to get a combination of both CPU and eGPU hardware to be classified. The results of the possibility of criteria will be made into two possibilities, namely "good" and "not good" then if there is new input or testing data it will be predicted that the data will go into the possibility of criteria based on Naïve Bayes calculations. The following picture of the research flow is explained in the Figure 1:

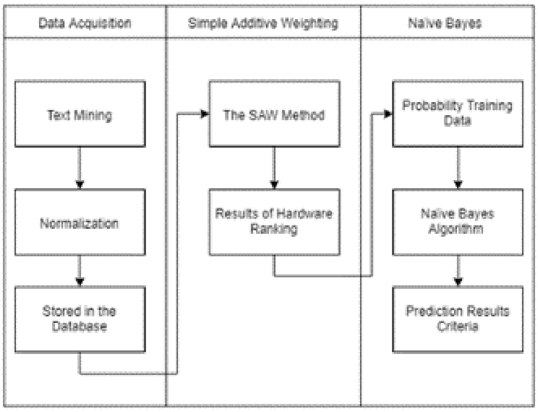

Figure 1 Reasearch Flow

In the research flow that has been made in Figure 1, then we will explain in more detail about how the implementation of the research flow, we use methods from the related literature for its implementation.

3.1 Data Acquisition

The data that has been obtained in the text mining process from Techpowerup, Geekbench and Amazon in accordance with the attributes obtained.

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3.2 Simple Additive Weighting (SAW)

To find out the best CPU and eGPU, it is necessary to carry out the calculation stages. These stages are as follows:

a. Determination of criteria
   The CPU determines the criteria for Cores (C1), Thread (C2), Base (C2), Clock (C4), and TDP (C5). For eGPU, the criteria for Memory (C1), Bit Rate (C2), GPU Clock (C3), and Memory Clock (C4) are determined.
b. Defines a Fuzzy number
   The predefined fuzzy numbers are 0.2 = Not Good, 0.3 = Good, 0.4 = Very Good
c. Criterion weights
   Give the weight of each criterion that has been made
d. Specifies the match table
   The CPU and eGPU alternatives will be entered in the match table
e. Make a decision matrix
   Creating a matrix for calculating alternative weights and criteria weights
f. Decision matrix normalization
   Normalizing the decision matrix
g. Ranking
   To find out the ranking of the best CPU and eGPU alternatives

The results of ranking all CPU data are then sorted by the largest value as shown in the following Table 1 :

Table 1 AMD 2017 CPU Ranking Results

Alternative	Value	Rank
Ryzen Threadripper 1950X	1.00	1
Ryzen Threadripper 1940X	1.00	1
A12-9800	0.87	3
A6-9550	0.87	3
Athlon X4 970	0.87	3
…	…	…
Ryzen Threadripper 1920	0.70	20

From the results of the above calculation it can be concluded that the CPU for 2017 AMD Ryzen Threadripper 1950X and Ryzen Threadripper 1940X both get the first rank because the ranking values are the same so there are two rank one.

Next do the same method until intel 2019 for the CPU. Following are the results of the SAW method on eGPU in 2017 AMD as in Table 2 below:

Table 2 2017 AMD eGPU Ranking Results

Alternative	Value	Rank
Radeon Pro SSG	0.89	1
Radeon Vega Frontier Edition	0.89	2
Radeon Vega Frontier Edition Watercooled	0.89	2
Radeon Instinct MI25	0.88	4
Radeon Instinct MI25 MxGPU	0.88	4
…	…	…
Radeon 530 Mobile	0.24	52

In the calculation of the eGPU Radeon Pro SSG ranking, the first rank is 0.89. Although the value is the same as the second rank the difference is 3 digits after the comma. For eGPU 2018 and 2019 have been calculated using the same method.

3.3 Naïve Bayes

Based on the SAW results, the calculation is only done based on the type of hardware with CPU or eGPU limitations and there is no combination of the two hardware. The limitation that we use is to use the price limit of the combination of the two hardware and we make it into three possibilities, namely with a price limit of Rp. 5,000,000.00 which we give a label Cheap, price of Rp. 10,000,000.00 with a medium label and the last Rp. 15,000 .000.00 with the label Expensive. Next we will classify into the criteria of "good" and "not good" based on the combination of the two hardware. Classification is done to find out if there is a hardware input that has never been trained and to find out the possibility of classification of the hardware input.

From the total CPU data obtained, we filter the CPU used for Naïve Bayes calculations by limiting the data based on the price range described, and not using CPU data that has a type only used for laptops. In eGPU data we use data based on price ranges and use external GPU or eGPU types so that the training data we use are 173 CPU data from a combined total of AMD and Intel brands, 64 eGPU data from a combined total of AMD and NVIDIA brands. In the process of labeling the dataset in the dataset training as many as 3,415 data, the labeling is based on a range of prices, criteria namely the value of ranking in the SAW process, as well as a combination of the two hardware based on the year of release to anticipate differences in the serial port when combined with different years, the data labeling is explained in Table 3:

Table 3 Labeling Training Data and providing criteria

ID	CPU	eGPU	Price	Criteria
1	Ryzen 7 1700	GeForce GT 1030	Cheap	Good
2	Ryzen 7 1700	Radeon RX 460 1024SP	Cheap	Good
3	Ryzen 5 1600X	GeForce GT 1030	Cheap	Not Good
…	…	…	…	…
3471	Intel Core i5-9400F	Radeon VII	Expensive	Good

After training the data it can be concluded that there is a set of data that has different characteristics in each condition, which will make it possible to make classifications if there is a new data input that wants to know its characteristics. The following diagram that explains the possible criteria at the specified price limits is shown in Figure 2.

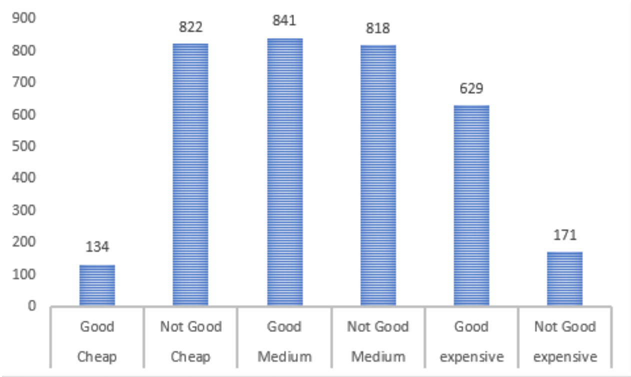

Figure 2 Criteria probability on price range

Figure 2 shows that there are 3,415 separate data based on prices and then broken down into per criteria so as to produce a good detail probability at a bargain price of 134 data, a bad probability at a low price of 822 data, a good probability at a moderate price of 841 data, a probability of not good at cheap prices as much as 818 data, good probability at expensive prices as much as 629 data, probability is not good at cheap prices as much as 171 data. If summarized further and addressed to find out the total number of probability criteria "Good" and "Not Good" then it can be seen in Figure 3.

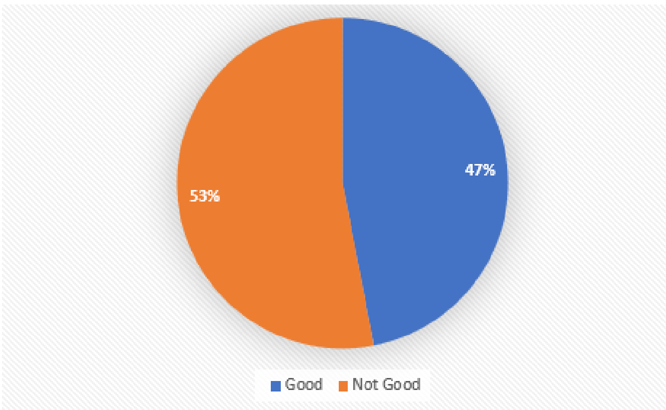

Figure 3 Chart of Total Probability Criteria

Figure 3 shows that the Criteria Probability of 3,415 data has a Good Criteria Probability of 1604 (47%) and a Not Good Criteria Probability of 1811 (53%). These probabilities cover the total amount of data regardless of the total price limit of the CPU and eGPU.

The following is an example of calculating the classification using Naïve Bayes on Ryzen 3 3200G GeForce GTX 1660 hardware.

P (criteria = Good | X) = P (X | criteria = Good) x P (criteria = Good) = P (Good = Ryzen 3 3200G | criteria = Good) x P (Not Good = GeForce GTX 1660 | criteria = Good) x P (= Cheap | criteria = Good) x P (criteria = Good) = 0.00561097 x 0.02431421 x 0.08354115 x 0.46969253 = 0.00000535

P (criteria = Not Good | X) = P (X | criteria = Not Good) x P (criteria = Not Good) = P (Good = Ryzen 3 3200G | criteria = Not Good) x P (Not Good = GeForce GTX 1660 | criteria = Not Good) x P (= Cheap | criteria = Not Good) x P (criteria = Not Good) = 0.00552181 x 0.00000000 x 0.45389288 x 0.53030747 = 0.00000000

A n + 1 calculation occurs because the result of the previous calculation has a value of 0, the next calculation is as follows:

P (criteria = Good | X) = P (X | criteria = Good) x P (criteria = Good) = P (Good = Ryzen 3 3200G | criteria = Good) x P (Not Good = GeForce GTX 1660 | criteria = Good) x P (= Cheap | criteria = Good) x P (criteria = Good) = 0.00623441 x 0.02493766 x 0.08416459 x 0.46971027 = 0.00000615

P (criteria = Not Good | X) = P (X | criteria = Not Good) x P (criteria = Not Good) = P (Good = Ryzen 3 3200G | criteria = Not Good) x P (Not Good = GeForce GTX 1660 | criteria = Not Good) x P (= Cheap | criteria = Not Good) x P (criteria = Not Good) = 0.00607399 x 0.00055218 x 0.45444506 x 0.53028973 = 0.00000081

Because it happens n + 1 then likened every probability to the criteria plus 1 data to represent each criterion In this study, to make classifications into two criteria Good and Not Good. Then the results of calculations of probability per criteria shown in Table 4:

Table 4 Criteria probability

Criteria	Probability
Good	1605/3417 (0.4697)
Not Good	1812/3417 (0.5303)

The addition of a value of 1 for each possibility, then the probability value Good on the CPU also changes, the results of these changes can be seen in Table 5:

Table 5 Criteria probability Good at CPU

CPU	Criteria probability = Good
A10-9700	15/1776 (0.0084)
A10-9700E	15/1776 (0.0084)
A12-9800	25/1776 (0.0141)
...	...
Ryzen Threadripper 2950X	5/1776 (0.0028)

Furthermore, changes in each value on the probability Not Good on the CPU will be shown in Table 6:

Table 6 Criteria probability Not Good at CPU

CPU	Criteria probability = Not Good
A10-9700	16/1983 (0.0081)
A10-9700E	16/1983 (0.0081)
A12-9800	9/1983 (0.0045)
...	...
Ryzen Threadripper 2950X	3/1983 (0.0015)

In probability Good on eGPU also be likened to adding a value of 1 every possibility, and therefore its value is also changed, the result of changes in the probability values shown in Table 7:

Table 7 Criteria probability Good at eGPU

eGPU	Criteria probability = Good
GeForce GT 1030	13/1668 (0.0078)
GeForce GTX 1050	7/1668 (0.0042)
GeForce GTX 1060	51/1668 (0.0306)
...	...
Radeon VII	24/1668 (0.0144)

Then, the value of probability Not Good in eGPU also changes, these changes are shown in Table 8:

Table 8 Criteria probability Not Good at eGPU

eGPU	Criteria probability = Not Good
GeForce GT 1030	63/1875 (0.0336)
GeForce GTX 1050	55/1875 (0.0293)
GeForce GTX 1060	23/1875 (0.0123)
...	...
Radeon RX 590	11/1875 (0.0059)

In the price criteria are divided into three alternatives namely cheap, medium, and expensive. The following changes in the probability Good at Price values for each alternative criteria are explained in Table 9 as follows:

Table 9 Criteria probability Good at Price

Price	Criteria probability = Good
Cheap	135/1607 (0.0840)
Medium	842/1607 (0.5240)
Expensive	630/1607 (0.3920)

Once there is also a change in the value of the probability Not Good on Prices, these changes are shown in Table 10:

Table 10 Criteria probability Not Good at Price

Price	Criteria probability = Not Good
Cheap	823/1814 (0.4537)
Medium	819/1814 (0.4515)
Expensive	172/1814 (0.0948)

Furthermore, the probability table and the results of the calculation of n + 1 can be calculated

P (X | criteria = Good) x P (criteria = Good) = 0.00000615 x 0.4697 = 0.00000288865

P (X | criteria = Not Good) x P (criteria = Not Good) = 0.00000081 x 0.5302 = 0.000000429462

The probability value on Good criteria is greater than the probability value of Not Good criteria. which shows the number 0.00000288865 is greater than 0.000000429462, so that Ryzen 3 3200G Input (Rp. 1,389,000) and GeForce GTX 1660 (Rp 3,410,000) (Cheap) have Classification results (Ryzen 3 3200G GeForce GTX 1660 Cheap) Criteria = Good.

Based on 3471 data, we divide it into 80% as many as 2776 as training data and 20% as much as 695 as testing data, then we calculate the accuracy of classification criteria. Tests are carried out to determine the performance of Accuracy, Precision, Recall and F1-Score on the Naïve Bayes algorithm in classifying the combination criteria of CPU and eGPU. The test results of Accuracy, Precision, Recall, and F1-Score with the Naïve Bayes algorithm can be seen in Table 11:

Table 11 Testing Table

Accuracy	Precision	Recall	F1-Score
0.768	1	0.764	0.866

The SAW application has been carried out to determine the ranking of CPU and eGPU data based on the highest criteria value in each price range, and the Naïve Bayes algorithm has been applied to classify whether the combination of the two hardware is a good criterion. So that making recommendations from existing rankings can meet the user's needs to select CPU and eGPU hardware at the entered price range to provide maximum recommendation results.

Based on Table 18, the results of testing the Naïve Bayes algorithm in its application to testing to classify the combination of CPU and eGPU, we carried out on 20% of the testing data produced quite good results on the value of F1-Score with a value of 0.866.

4. CONCLUSIONS

From our research it can be concluded that the SAW method is used to obtain CPU and eGPU hardware ranking based on the hardware brand, ranking is influenced by weights that have been determined on the criteria in the SAW process. The results each year have ranked number 1 with the most superior ranking. In testing conducted on the application of Naïve Bayes using 80% of the training, data has 2776 data and 20% of testing data has 695 data that will be tested for accuracy, precision, recall, and F1-score. For the results of tests that have been carried out get 0.78 accuracy results, precision 1, Recall 0.764, and F1-Score 0.866.

Suggestions for further research are to compare the accuracy against other classification algorithms so that the best algorithm can be found in providing the maximum recommendations. In this study, the combination of hardware implementation in the same year has been limited, but for future research suggestions, it is necessary to provide a limit for the combination of CPU and eGPU devices so that bottlenecks do not occur.

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