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The Concept Design of Rice Quality Detection System Using Model-Based System Engineering Approach

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Abstract. *Quality of rice is determined by several factors such as water content, broken grains, and whiteness. The approach often used for the measurement is manual, time-consuming, and prone to error. Therefore, this research proposes a faster and more accurate rice quality detection system using Model-Based System Engineering (MBSE) approach. System was based on the needs analysis presented through an activity diagram showing the components and activities flow. Logical architecture diagrams were also used to structurally describe system logic to be further abstracted to the physical architecture stage. Moreover, machine learning techniques were used to simulate rice quality data analysis using the decision tree classification with the Iterative Dichotomizer 3 (ID3) algorithm. The simulation was applied to 200 supervised random datasets divided into 80% training and 20% test data with a focus on three attributes, including water content, broken grains, and whiteness. System design was developed using Visual Paradigm Community Edition software and the data were analyzed through the application of R software. The ID3 algorithm simulation produced rice quality detection system with a 92.5% accuracy rate, where 53% of rice was classified as good and 47% as bad. The proposed conceptual design for rice quality detection can be a starting point for the development of an industrial-scale system design.*
Keywords: *design concept; rice quality; classification; decision tree.*

Type of the Paper: Regular Article.

1. Introduction

Rice is the staple food for most of the population in the world and has been observed to be easily damaged, specifically when stored for a long time, due to aging [1]. Several previous research have been conducted to determine quality of rice based on the size and shape [2], changes in color [3], changes in water content [4], chalky area analysis [5], cooking sensory [6,7], pasting properties [8], texture characteristics [9], amino acid [10], and acid value [11]. The process was observed to generally require time-consuming laboratory tests. Meanwhile, the storage of rice in large volumes for long period is susceptible to quality degradation. The trend shows the need to design a classification system to quickly determine quality level of rice.

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Model-Based Systems Engineering (MBSE) is an improvement over the traditional approach of Document-Based Systems Engineering (DBSE) which requires storage project and design information in documents to be manually managed and transferred between system elements. The traditional DBSE approach is labor-intensive and consists mainly of manual analysis, review, and inspection [12,13]. Meanwhile, MBSE implements model formalization that supports system modeling and analysis in graphical form, which enhances information acquisition, analysis, sharing, and management more accurately [14]. The application of the new approach has been gaining interest as a proposed solution to making the task of systems engineering more convenient, specifically for large, complex projects [12]. These advantages have led to the wide adoption of MBSE in several industries requiring automation [15].

MBSE focuses on constructing model design through systems approach that emphasizes two factors, including communication and simulation. This approach can be used to provide rice quality detection system through the stages of model graphical design using system Modeling Language (SysML) [16]. The first stage is the application of case, activity, and logical architecture diagrams as well as the functional aspect which can be further detailed in physical architecture diagrams [17]. The next stage is to perform simulations using machine learning to classify rice quality through the application of a decision tree and the Iterative Dichotomizer 3 (ID3) algorithm based on the attributes of moisture content, broken grain, and whiteness. The ID3 algorithm developed by J Ross Quinlan can be used to compile a top-down decision tree from top to bottom, starting with the attribute to be checked first and placed as root [18,19]. The trick is to evaluate all existing attributes using a statistical measure widely used in information gain to determine the effectiveness of each in classifying a collection of data samples. Therefore, this research aimed to develop rice quality detection system using MBSE and the ID3 algorithm. The MBSE approach was used to present the conceptual design graphically, conduct needs analysis among system stakeholders, as well as comprehensively describe the workflow and logical structure of rice quality detection system.

2. Materials and methods

2.1. Materials

This research was conducted using 200 data consisting of three attributes, including water content, whiteness, and broken grains to classify rice quality into two levels, good and bad. The water content and broken grains values presented in Table 1 are based on the Indonesian National Standard No. 6128 of 2020 [20] while the whiteness is the milling degree conversion determined through the Indonesian National Standard No. 6128 of 2015 [21]. The value of each attribute was determined using the "the=RandBetween'' formula with Microsoft Excel software.

Table 1. Attribute values to the prediction model

	Variable	Min	Max	Target
Predictors	Water content (%)[a*]	12.96	15.09	Min
	Whiteness [b*]	43.57	54.47	Max
	Broken grains (%)[a*]	4.25	35	Min

a* : Refer to literature [20]; b* : Refer to literature [21]

2.2. Methods

2.2.1. MBSE

The Community Edition of Visual Paradigm software was used to describe design of rice quality analysis system using the MBSE approach. The initial steps were to develop a needs analysis between the elements in system using a case or activity diagram to visualize the sequence of activities. This was followed by the development of logical architecture diagrams to translate activity diagrams into operational system simulations. The next step was to conduct simulations using machine learning to classify rice quality using a decision tree and the ID3 algorithm based on the moisture content, broken grain, and whiteness attributes.

2.2.2. Decision Tree Classification

Decision tree learning is considered part of the most popular classification techniques in machine learning [22]. The preference for the ID3 decision tree algorithm was based on the ability to produce a simple and efficient tree with a minor depth [19]. The classification model uses a tree structure where each node represents an attribute and the branch shows the value. In contrast, the leaves represent the top node class called the root which is the most influential attribute of the tree [19]. This is because the variable with the highest information gain value is set as the root. In ID3, the feature importance shows the frequency of attributes in building a tree through the information gain value, A, mathematically represented as follows (1) [19].

$$G(S,A) = E(S)\sum_{i=1}^{m} \text{fs (Ai)E (SAi)} \tag{1}$$

where, G(S, A) is the gain of attribute A in S, E(S) is entropy (S), S is the sample space used for training data, m is the number of different values of attribute A in S, fs (Ai) is the proportion of the value of Ai as the value of the attribute A in S, and SAi is A subset of S containing all items where the value of A is Ai. Meanwhile, entropy can be calculated through the following (2).

$$\text{Entropy (S)} = \sum_{i=1}^{n} \text{fs (j)log2 fs(j)} \tag{2}$$

where, n is the number of different attribute values in S, and fs(j) is the proportion of value to j in S.

In this design concept, the data consisting of three critical and influential components, including water content, whiteness, and broken grain determined based on the Indonesian National

Standard on rice [20,21], were simulated to classify rice quality. The data were analyzed using the ID3 algorithm decision tree classification with R software version 4.1.3. This was achieved by dividing the 200 supervised random datasets in Table 1 into 80% training and 20% test data.

3. Results and Discussion

3.1. MBSE

Design concept for rice quality detection system developed through the MBSE approach is presented in the following Fig. 1. Activity diagram is often used to model the activities of an operation [16]. It focuses on developing the activity flow of a case to model the behavior of system consisting of several actions, starting from the initial node to the destination node. The process requires objects moving from one activity to another in system flow and some conditions need to be selected to determine a decision.

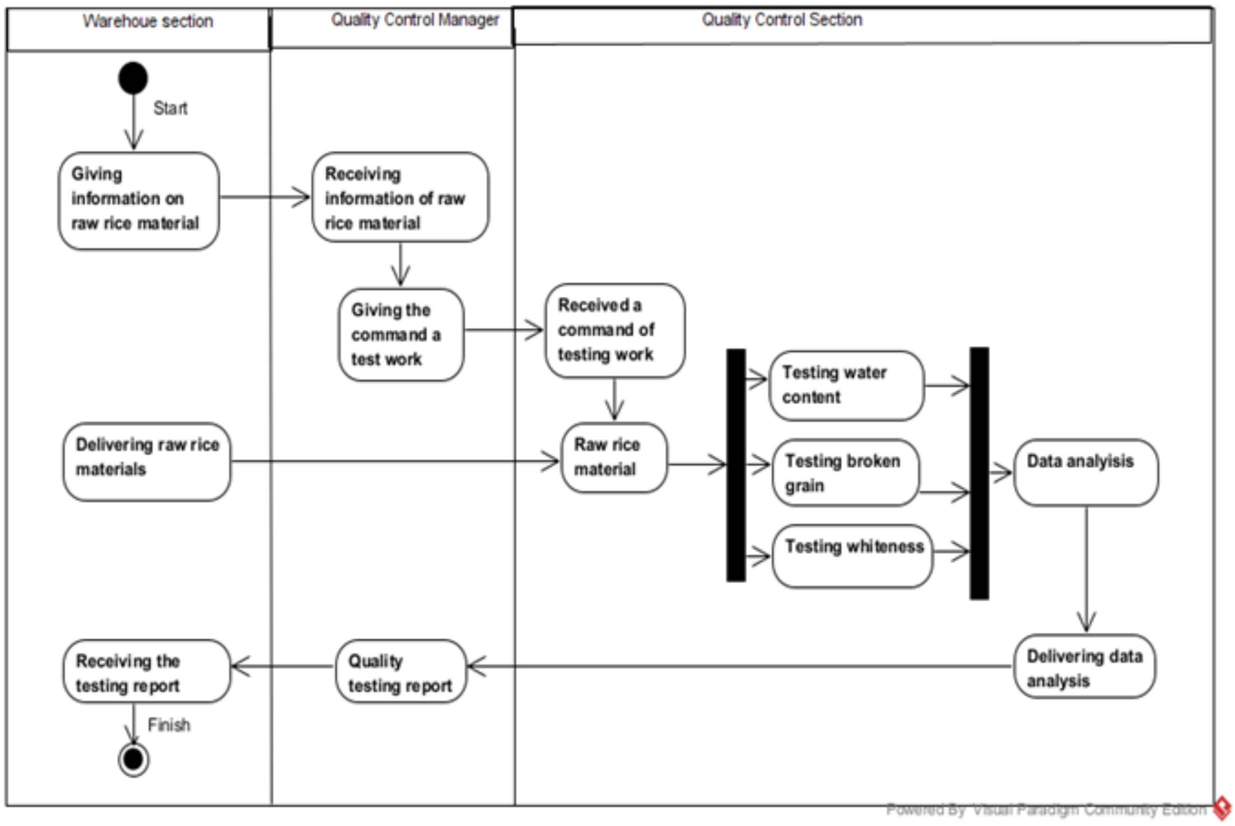

Fig. 1. Activity diagram of rice quality detection system

The figure shows the initial node starts from the warehouse section which provides information on rice stocks to be tested by Quality Control (QC) manager and this is followed by the issuance of a test work order to the QC department. Quality was later tested by the department with a focus on water content, broken grain, and whiteness which were assessed through a parallel format.

The application of MBSE ensures easier coordinated system design and development between teams from multiple disciplines to optimize costs, schedules, and performance by processing and sharing information with other stakeholders [23]. Tschirner et al. [24] further stated that the inclusion of MBSE in industrial applications required an interdisciplinary approach instead of an individual design concept. For example, Lemazurier et al. [25] used systems approach to design complex systems into the functional architecture of the Nuclear Power Plant and Barrett et al. [26] also used MBSE to design passenger train operations.

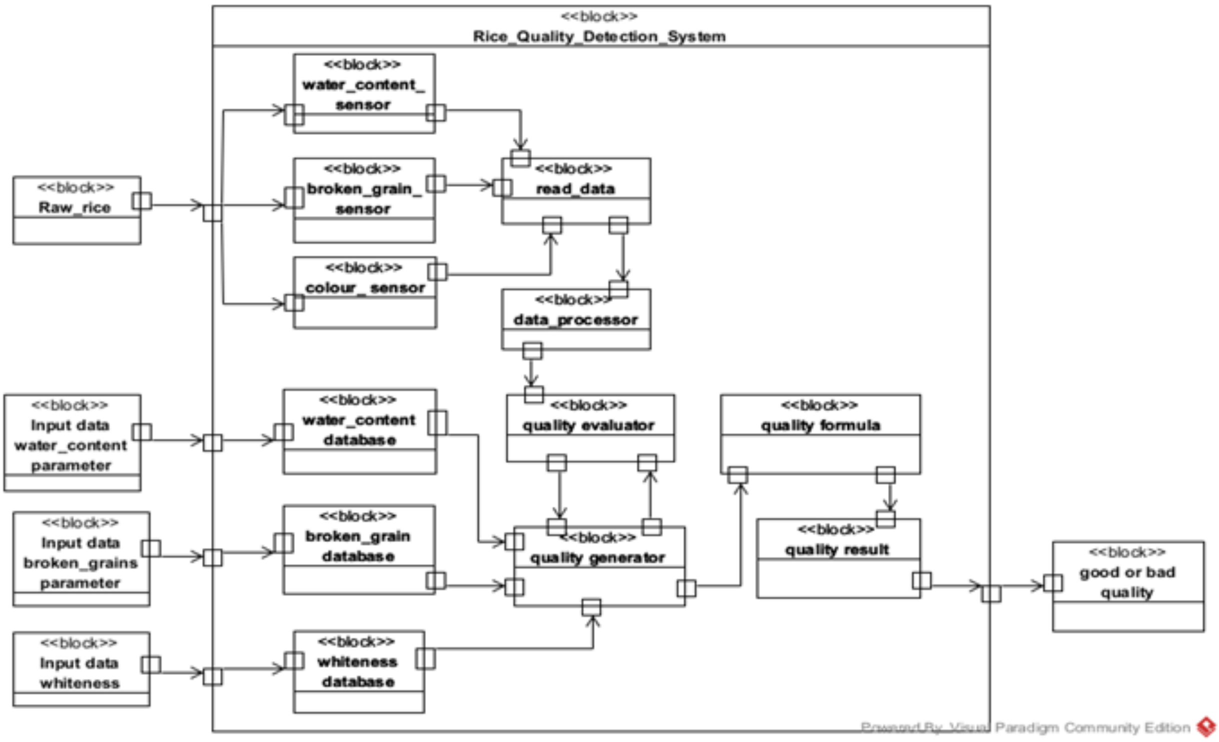

Fig. 2. Logical architecture diagram of rice quality detection system

This rice quality detection system design was simulated through the application of different types of sensors to read data for each attribute. The focus was on the measurement of the water content [27], color [28], and weight of broken grains [27]. The data obtained were processed with R software to determine quality of rice by serving as the reference parameter in the decision tree classification with the ID3 algorithm. The QC manager later sent the report on rice quality test to the warehousing department for further handling. The advantage of modeling through MBSE was the opportunity provided to describe the behavior of the present and next system or activity through activity diagrams compiled based on the analysis of stakeholder needs.

The next step was to describe system logic structurally as a basis for the physical design through a logical architecture diagram presented in Fig. 2. The diagram is an abstraction showing the link between functional and physical architecture. It describes the functional flow of rice quality detection system that needs to be further translated into physical architecture [17]. System was conceptually and abstractly divided into three main blocks, including input, process, and output, and worked functionally through a sequence of steps to detect rice quality. The input block was data on color, moisture content, and broken grains read by the sensor which were forwarded to the process block to evaluate quality based on the predetermined criteria.

The functional design concept was developed to ensure the automatic operation of system in order to detect rice quality quickly and efficiently. This was in line with the suggestion of Feldmann et al. [15] that the implementation of MBSE in automated production systems was profitable and efficient. Moreover, the development stage allowed stakeholders to translate the necessary requirements to designers and engineers.

Automation systems are expected to continue growing more complex due to the increasing need for flexibility in the industry. This led Fay et al. [29] to develop an approach to support MBSE of distributed manufacturing automation systems. MBSE has also been used in the textile production automation process [30] due to the graphical modeling that allows effective and easier communication and workflows between stakeholders. The approach can be developed to design a continuous complex process flow as well as large and varied datasets for other products or commodities [15].

3.2. Decision Tree Classification

The next stage of the research was to simulate the data processed using ID3 algorithm decision tree classification with R software version 4.1.3. This was achieved through the application of 200 supervised random datasets which were divided into 80% training and 20% test data as presented in Table 1.

```
data22=read.delim("clipboard")
data22
library(party)
View(data22)
>dim(data22)
[1] 200   4
>n <- round(nrow(data22)*0.80);n
[1] 160
>dim(data.train)
[1] 160   4
>dim(data.test)
[1] 40  4
>library(rpart)
>library(rpart.plot)
>fit <- rpart(rice.quality~., data = data.train, method = 'class')
>summary(fit)
Call:
rpart(formula = rice.quality ~ ., data = data.train, method = "class")
  n= 160
          CP nsplit rel error    xerror       xstd
1 0.61643836      0 1.0000000 1.0000000 0.08630545
2 0.06849315      1 0.3835616 0.4520548 0.07010936
3 0.01000000      3 0.2465753 0.3287671 0.06187172

Variable importance
broken.grains water.content     whiteness
           58            28            14
```

The visualization of the data in the R program is presented in the following Fig. 3.

```
R 4.1.3 · ~/Latihan/
> data22
   water.content whiteness broken.grains rice.quality
1           13.6      49.6          12.7         good
2           13.7      47.4          26.7          bad
3           13.8      52.2          19.9         good
4           14.0      52.5          12.5         good
5           14.4      43.6          28.0          bad
6           14.0      52.6          18.6         good
7           14.6      50.4          21.5          bad
8           14.9      50.4          21.7          bad
9           13.8      54.2           7.5         good
10          14.2      47.5          31.2          bad
11          15.0      52.1          25.4         good
12          14.1      51.6          25.3         good
13          13.6      48.8           9.1         good
14          15.1      48.1          24.4          bad
15          14.9      51.4          10.3         good
16          14.7      47.7          19.8         good
17          14.4      53.0          15.9          bad
18          14.1      51.1          24.2          bad
```

```
Console  Terminal  Jobs
R 4.1.3 · ~/Latihan/
172          13.5      47.2          10.7         good
173          14.7      49.6          12.1         good
174          13.8      49.9          18.9         good
175          14.7      47.1          28.0          bad
176          14.9      48.8          28.7          bad
177          14.3      53.3          19.0          bad
178          13.7      53.2          15.2         good
179          13.6      51.7          16.4         good
180          14.5      51.7           5.3         good
181          15.1      48.4          31.8          bad
182          14.1      51.4          20.3         good
183          14.0      50.1          14.3         good
184          14.6      51.2          31.9          bad
185          13.7      44.3          23.8          bad
186          14.2      48.2          28.9          bad
187          14.7      48.4          19.6          bad
188          13.6      49.8          20.7         good
189          13.6      54.2          12.5         good
190          13.5      51.3          18.7         good
191          14.1      51.2          12.5         good
192          14.2      51.1          10.8         good
193          14.5      53.0          15.3         good
194          13.5      49.8          18.1         good
195          14.2      47.0           5.1         good
196          13.7      51.8          16.9         good
197          13.6      54.1           6.0         good
198          14.4      51.5          31.1          bad
199          14.4      51.4          14.3         good
200          14.9      44.0          17.8          bad
>
```

Fig. 3. The data visualization in R

The attribute that recorded the highest number of variables was broken grains with 58% and was defined as the roots followed by water content at 28% and whiteness at 14. Moreover, Sharma and Srivastava [31] stated that the output of the decision tree in R could be visualized through the rpart.plot package. Model visualization of the decision tree produced for rice quality detection system is presented in the following Fig. 4.

```
Node number 1: 160 observations, complexity param=0.6164384
  predicted class=good expected loss=0.45625 P(node) =1
    class counts:    73    87
   probabilities: 0.456 0.544
  left son=2 (59 obs) right son=3 (101 obs)
  Primary splits:
      broken.grains < 21.65 to the right, improve=33.78119, (0 missing)
      water.content < 14.15 to the right, improve=23.11250, (0 missing)
      whiteness     < 50.85 to the left, improve=13.93763, (0 missing)
  Surrogate splits:
      water.content < 14.75 to the right, agree=0.669, adj=0.102, (0 split)
      whiteness     < 47.55 to the left, agree=0.644, adj=0.034, (0 split)

Node number 2: 59 observations
  predicted class=bad   expected loss=0.1186441 P(node) =0.36875
    class counts:    52     7
   probabilities: 0.881 0.119

Node number 3: 101 observations, complexity param=0.06849315
  predicted class=good expected loss=0.2079208 P(node) =0.63125
    class counts:    21    80
   probabilities: 0.208 0.792
  left son=6 (35 obs) right son=7 (66 obs)
  Primary splits:
      water.content < 14.25 to the right, improve=12.0171100, (0 missing)
      whiteness     < 48.5  to the left,  improve= 7.6509160, (0 missing)
      broken.grains < 17.6  to the right, improve= 0.8702323, (0 missing)
  Surrogate splits:
```

```
    whiteness    < 46.6  to the left,  agree=0.733, adj=0.229, (0 split)
    broken.grains < 20.85 to the right, agree=0.673, adj=0.057, (0 split)

Node number 6: 35 observations,    complexity param=0.06849315
  predicted class=bad   expected loss=0.4571429  P(node) =0.21875
    class counts:    19    16
   probabilities: 0.543 0.457
  left son=12 (16 obs) right son=13 (19 obs)
  Primary splits:
    whiteness    < 48.8  to the left,  improve=4.285902, (0 missing)
    water.content < 14.85 to the right, improve=3.571429, (0 missing)
    broken.grains < 15.85 to the right, improve=1.136134, (0 missing)
  Surrogate splits:
    water.content < 14.75 to the right, agree=0.714, adj=0.375, (0 split)
    broken.grains < 12.35 to the right, agree=0.600, adj=0.125, (0 split)

Node number 7: 66 observations
  predicted class=good  expected loss=0.03030303  P(node) =0.4125
    class counts:     2    64
   probabilities: 0.030 0.970

Node number 12: 16 observations
  predicted class=bad   expected loss=0.1875  P(node) =0.1
    class counts:    13     3
   probabilities: 0.812 0.188

Node number 13: 19 observations
  predicted class=good  expected loss=0.3157895  P(node) =0.11875
    class counts:     6    13
   probabilities: 0.316 0.684

>library(rattle)
>fancyRpartPlot(fit)
```

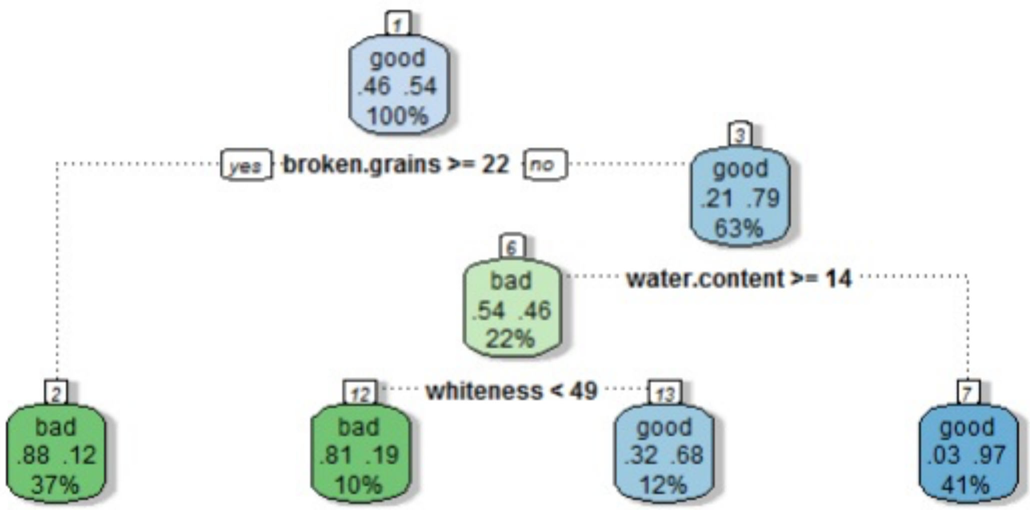

Fig. 4. Decision tree of rice quality detection system

Broken grains attribute was placed at the top of the decision tree diagram due to the role as the root. Decision Note 1 which was the broken grains attribute was divided into two parts, including rice with broken grains >22 categorized as bad quality at 37% while 63% was considered good with a probability level of 79% due to the possible existence of some poor grains through water content. Decision Note 3 was for the moisture content, rice with < 14 was 41% and categorized as good quality at a 97% probability. Meanwhile, rice with moisture content > 14 was 22%, classified as bad quality at a 46% probability, and further selected in Decision Note 6 through the whiteness attribute as the selector. In Decision Note 6, rice with whiteness <49 was 10% and categorized as bad quality while only 12% was classified as good quality. The data processing results further showed the ability of system to detect 53% of rice to have good quality while 47% was bad.

The confusion matrix is model evaluation for making predictions and classifications [32]. This is due to the ability of model to summarize the actual and predicted tables consisting of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The confusion matrix analysis was applied in this research to validate the ID3 algorithm using 40 test data with the results presented in Table 2.

```
>prediksi = predict(fit, newdata = data.test, type = "class")
>table(prediksi, data.test$rice.quality)
prediksi bad good
   bad     15   2
      good   1   22
```

Table 2. Confusion matrix of decision tree-ID3

		actual value	
		Good (1)	Bad (0)
Predictive value	Good (1)	TP = 22	FP = 1
	Bad (0)	FN = 2	TN = 15

where, TP is when the prediction and actual value are equally positive, TN is when the prediction and actual value are equally negative, FP is when the actual value is negative but the prediction is positive, and FN is when the actual value is positive but the prediction is negative. Moreover, accuracy is the primary parameter often used to determine the capacity of model to predict correctly using datasets [32]. It can also be applied to determine the performance of model using the following equation (3).

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{FN} + \text{TN})}\ x\ 100\% \tag{3}$$

The application of the equation (3) showed that the accuracy of the prediction model was 92,5%. Previous research had also applied other methods to determine the accuracy of rice quality detection system. For example, Hamzah and Mohamed [33] applied Artificial Neural Network (ANN) to classify rice using size and shape parameters with an accuracy of 98.7%. Meizenty et al. [34] also used a digital image with the K-Nearest Neighbors (KNN) at a 42.64% accuracy while Son and Thai-nghe [35] measured whole and broken rice with the Convolutional Neural Network (CNN) at 84.30%. Farahnakian et al. [36] also reported 99,6% accuracy through the adoption of the EfficientNet deep model to classify rice grain images. The trend showed that design concept from this research could applied at the operational stage of rice quality analysis. However, there is a need for the physical architecture stage to detail each component or equipment needed according to field conditions to ensure the system is operated in real terms.

4. Conclusions

In conclusion, MBSE was used to easily develop a conceptual design for rice quality detection system starting from activity to logical architecture diagrams. The graphical modeling of the approach was advantageous due to the ability to simplify the understanding of communication and stakeholder workflows. Moreover, MBSE allowed the design of a continuous, complex process flow as well as the management of large and varied datasets for different products or commodities. Design could be conceptually applied on an industrial scale due to the possibility of operating rice quality detection system continuously. However, further processes were required to translate the logical architecture into a physical architecture diagram detailing each component of the equipment needed. The data analysis simulation conducted using the ID3 decision tree algorithm showed that the concept design was able to classify rice as 53% good and 47% bad quality. Moreover, the Confusion Matrix produced 92.5 % accuracy but the implementation of the concept design required further refining to the physical architecture diagram stage in order to have a comprehensive description of the technical requirements.

Data availability statement

The data supporting this study's findings are available from the first author, Purwa Tri Cahyana, upon reasonable request.

Authors' Contributions

Purwa Tri Cahyana developed the experimental design, conducted data collection, performed statistical analysis, interpreted the data, and drafted the paper; Noer Laily assisted with statistical analysis and interpretation of results; Erliza Noor and Hartrisari Hardjomidjojo assisted with interpretation of results; Titi Candra Sunarti reviewed the paper and approved the published version of the document.

Declaration of Competing Interest

The authors declare there was no known competing financial interests or personal relationships that could have appeared to influence the work reported.

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