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# Optimizing Deep Learning using Feature Selection for Accurate Health Insurance Claim Classification

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***Abstract –*** *Accurate prediction of health insurance claims is essential for improving hospital service quality, financial management, and operational decision-making. Health insurance claim data contains multiple attributes that may affect the performance and efficiency of classification models. Data mining techniques, particularly deep learning, are widely applied because of their ability to identify complex patterns in large datasets. However, the use of numerous attributes can increase model complexity and computational requirements. Therefore, feature selection can be applied to reduce data dimensionality while retaining relevant information for the classification process. This study aims to optimize a deep learning model using the Weight by User Specification method as a feature selection technique for classifying BPJS Health insurance claims. The dataset consists of 2,388 BPJS Health insurance claim records from Kumala Siwi Hospital, with variables including total rate, hospital rate, profit, diagnosis, and INACBG. The research process follows data preprocessing, data transformation, deep learning classification, feature selection, and model evaluation using a confusion matrix. Two classification models were evaluated: deep learning without feature selection and deep learning combined with Weight by User Specification. The results show that the deep learning model without feature selection achieved an accuracy of 98.87%, while the optimized model achieved 99.20%, representing an improvement of 0.33%. The classification error also decreased from 1.13% to 0.80%. These findings indicate that integrating feature selection with deep learning can improve classification accuracy and reduce classification error in BPJS Health insurance claim prediction. Therefore, weight by user specification combined with deep learning provides an effective approach for health insurance claim classification.*

***Keywords:*** *Deep learning; Feature Selection; Classification; Big Data; Optimization*

## I. INTRODUCTION

According to Presidential Regulation of the Republic of Indonesia Number 12 of 2013 concerning Health Insurance, health insurance provides protection so that participants can obtain health care benefits and meet their basic health needs. The Social Security Administering Body (BPJS) was established by the government to administer the National Health Insurance (JKN) program. In the implementation of the BPJS Health program, hospitals are required to manage claim submissions effectively and efficiently because the timeliness and accuracy of claim processing can affect hospital operations and financial management (Syah et al., 2025)

Health insurance claims are closely related to the continuity of hospital operations. Delayed or pending claims can affect hospital cash flow and may postpone the procurement of medicines, medical equipment, and the provision of employee performance incentives. Therefore, identifying claim patterns and predicting whether claims can be classified as worthy or pending is important for supporting hospital management in improving claim processing and maintaining the quality of health services (Syah et al., 2023). Hospitals require data and information to support planning and decision-making. Historical claim data can be analyzed to identify patterns associated with claim outcomes and provide useful information for improving claim management (Alkattan et al., 2025)

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Data mining provides various approaches for extracting useful information from multidimensional datasets. In the healthcare domain, data mining has been applied to identify patterns and support decision-making based on large volumes of clinical and administrative data (Khrisna Wardhani et al., 2025). One classification approach that can be applied to complex datasets is deep learning. Deep learning uses multiple layers of artificial neural networks to learn representations and patterns from data and has demonstrated its ability to perform classification tasks in various domains .Its ability to automatically learn complex patterns makes deep learning a potential approach for classifying health insurance claim data (Laber et al., 2022).

Various recent studies confirm that deep learning is highly effective in predicting healthcare costs and insurance claim status due to its ability to model non-linear interactions and high-dimensional data dynamics (Lee et al., 2026). However, most real-world health insurance claim data have a tabular structure that is susceptible to feature heterogeneity and irrelevant attributes. Without robust preprocessing and feature selection, deep learning algorithms can experience overfitting or simply reach their performance ceiling without providing significantly better results than traditional regression models(Stephan et al., 2025) . Therefore, optimization through feature selection and weighting becomes a crucial step to filter the most influential information in determining claim status(Mielke et al., 2026) .

Besides the challenges of tabular data complexity, the application of deep learning in the insurance and healthcare domains is often faced with transparency issues due to the opaque (black-box) nature of the models. High predictive accuracy frequently does not align with the model's ability to explain the specific reasons behind a decision(Jung & Jung, 2026). In the context of hospital management, this transparency is essential so that claim predictions can be trusted, economically understood, and audited. An approach that integrates feature selection and specific weighting (feature weighting) is highly recommended because it not only optimizes model performance but also provides a clear interpretation of the main factors influencing claim status decisions(Knox et al., 2026) .

However, the performance of deep learning can be affected by the characteristics and number of attributes used in the dataset. A dataset containing a large number of attributes may increase model complexity and computational requirements and may introduce irrelevant or redundant information into the learning process(Nakamura et al., 2026) . Feature selection is therefore an important preprocessing and optimization approach for identifying relevant attributes and reducing the dimensionality of the dataset. Feature selection can remove unnecessary, irrelevant, or redundant attributes while retaining information that contributes to classification performance (Niu et al., 2024).

Feature selection methods can generally be categorized into filter, wrapper, and embedded approaches. Filter methods evaluate the relevance of features independently of the classification algorithm, whereas wrapper methods evaluate subsets of features based on classifier performance. Embedded methods perform feature selection during the model learning process(Shawosh et al., 2026) . The selection of an appropriate feature selection method is important because different methods may produce different feature subsets and consequently affect the performance of the classification model. Previous studies have investigated feature selection for improving classification performance in various application domains (Mienye & Jere, 2024).

In addition to conventional feature selection approaches, Weight by User Specification provides a method for assigning weights to attributes based on user-defined specifications. This approach can be used to identify and retain attributes considered important for the classification process. In the context of health insurance claims, variables such as total rate, hospital rate, profit, diagnosis, and INACBG contain information that may contribute to distinguishing worthy and pending claims. However, the application of Weight by User Specification in combination with deep learning for BPJS Health insurance claim classification remains limited in the context of the dataset used in this study (Alkattan et al., 2025).

Based on the literature reviewed, previous studies have demonstrated the potential of deep learning for classification and the benefits of feature selection in reducing feature dimensionality and improving model performance(Hussain et al., 2026) . Nevertheless, there is still a need to investigate whether a user-specified feature weighting approach can improve the performance of deep learning when applied to BPJS Health insurance claim classification. Therefore, this study aims to optimize a deep learning model using the Weight by User Specification feature selection method for classifying BPJS Health insurance claims into worthy and pending categories (Vijayalaskhmi et al., 2022).

The contribution of this study is the integration of Weight by User Specification with deep learning and the evaluation of its effect on classification performance using BPJS Health insurance claim data from Kumala Siwi Hospital. The performance of the deep learning model without feature selection is compared with the optimized deep learning model using Weight by User Specification. Model

performance is evaluated using a confusion matrix and classification accuracy. Through this approach, the study seeks to determine whether feature selection can improve the accuracy of deep learning for health insurance claim classification and provide a more effective approach for supporting hospital claim management.

# II. METHODS

### 2.1 Research Design

This study employed an experimental quantitative approach to evaluate the effect of feature selection on the performance of a deep learning classification model for BPJS Health insurance claims. The experiment compared two classification models using the same claim dataset and classification target. The first model applied deep learning directly to the preprocessed dataset, while the second model applied Weight by User Specification as a feature selection method before classification using deep learning.

The research procedure consisted of data collection, data preprocessing, feature selection, deep learning classification, and model evaluation. The two experimental conditions were evaluated using the same classification procedure to determine whether the application of feature selection improved classification performance.

### 2.2. Data Collection

The dataset consisted of 2,388 BPJS Health insurance claim records obtained from Kumala Siwi Hospital. The records were used to classify health insurance claims into two classes: Worthy and Pending. The dataset included claim-related attributes such as total rate, hospital rate, profit, diagnosis, and INACBG. The target variable in this study was the claim status, with two possible classes:

- **Worthy**: a claim classified as eligible/acceptable.
- **Pending**: a claim classified as requiring further handling or having a pending status.

The dataset was prepared before classification to ensure that the records and attributes could be processed by the classification model. The use of 2,388 records is consistent with the confusion matrices reported for both experimental models. The deep learning model produced 2,319 + 12 + 15 + 42 = 2,388 observations, while the deep learning model with feature selection produced 2,327 + 12 + 7 + 42 = 2,388 observations.

### 2.3 Dataset Attributes

The attributes explicitly identified in the manuscript were total rate, hospital rate, profit, diagnosis, and INACBG. These attributes were used as predictor variables for claim classification, while the claim status was used as the target variable.

Table 1. Dataset Attributes Used in the Classification

| No. | Attribute | Role | Data Type* |
|---|---|---|---|
| **1** | Total Rate | Predictor | Numeric |
| **2** | Hospital Rate | Predictor | Numeric |
| **3** | Profit | Predictor | Numeric |
| **4** | Diagnosis | Predictor | Categorical |
| **5** | INACBG | Predictor | Categorical |
| **6** | Claim Status (Worthy/Pending) | Target | Categorical |

*The data types should be verified against the original dataset/RapidMiner attribute settings before final submission.

The five predictor attributes above are the variables explicitly mentioned in the manuscript as part of the dataset. If additional attributes were actually included in the RapidMiner experiment, those attributes must also be added to Table 1 so that the table represents the complete experimental dataset.

### 2.4 Data Preprocessing

Data preprocessing was conducted before the classification process. The preprocessing consisted of data cleaning, data integration, and data transformation. Data cleaning was performed to identify and remove or handle erroneous records so that only appropriate records were used in subsequent analysis. Data integration was conducted to prepare the required claim attributes in an integrated dataset. Data transformation was then performed to adjust the data representation to the requirements of the classification process.

After preprocessing, the dataset was divided into training and testing data. The same data partition was used for the two experimental conditions to enable a direct comparison between the deep learning model without feature selection and the deep learning model with feature selection. The manuscript confirms that the data were divided into training and testing data before the two experimental trials were conducted.

### 2.5. Feature Selection Using Weight by User Specification

Weight by User Specification was applied as the feature selection method in the second experimental condition. The method assigns user-defined weights to attributes according to their specified importance. The resulting feature weights were used to determine the attributes retained for the subsequent deep learning classification.

The feature selection process was applied to the predictor variables before the data were processed by the deep learning classifier. The purpose was to reduce the number of attributes considered by the model while retaining attributes considered relevant to the classification of Worthy and Pending claims.

Table 2. User-Defined Feature Weights

| No. | Attribute | User-Defined Weight | Selected for DL |
|---|---|---|---|
| **1** | Total Rate | [Insert Actual Weight] | [Yes/No] |
| **2** | Hospital Rate | **[Insert Actual Weight]** | **[Yes/No]** |
| **3** | Profit | **[Insert Actual Weight]** | **[Yes/No]** |
| **4** | Diagnosis | **[Insert Actual Weight]** | **[Yes/No]** |
| **5** | INACBG | **[Insert Actual Weight]** | **[Yes/No]** |

The numerical weights in Table 2 must be taken directly from the Weight by User Specification configuration used in the original experiment. They should not be inferred from the classification results because the manuscript currently does not report the assigned numerical weights.

### 2.6 Deep Learning Model

Deep learning was used as the classification algorithm in both experimental conditions. The first experiment used the preprocessed attributes directly as inputs to the deep learning classifier. The second experiment used the attributes selected through Weight by User Specification as inputs to the same classification approach.

The model was trained to classify each claim into one of two target classes, namely Worthy and Pending.

Table 3. Deep Learning Configuration

| Parameter | **Configuration Used** |
|---|---|
| **Classification algorithm** | Deep Learning |
| **Input variables** | Dataset attributes / selected attributes |
| **Target variable** | Claim Status |
| **Target classes** | Worthy, Pending |
| **Number of input neurons** | [Insert Actual Value] |
| **Number of hidden layers** | [Insert Actual Value] |
| **Neurons per hidden layer** | [Insert Actual Value] |
| **Activation function** | [Insert Actual Value] |
| **Learning rate** | [Insert Actual Value] |
| **Training cycles / epochs** | [Insert Actual Value] |
| **Batch size** | [Insert Actual Value, If Applicable] |
| **Training/testing split** | [Insert Actual Split] |
| **Random seed** | [Insert Actual Value, If Used] |

The values in Table 3 must correspond to the actual Deep Learning operator configuration used in the experiment. The current manuscript confirms the use of deep learning but does not report these architecture and hyperparameter values. Therefore, these values should be retrieved from the original RapidMiner process rather than estimated.

### 2.7 Experimental Procedure

Two experiments were conducted using the prepared BPJS Health insurance claim dataset.

- **Experiment 1: Deep Learning (DL).**

  The preprocessed dataset was directly processed using the deep learning classification method. The model was trained using the training data and subsequently evaluated using the testing data.
- **Experiment 2: Deep Learning with Feature Selection (DL+FS).**

  The preprocessed dataset was first processed using Weight by User Specification. The selected attributes were then used as input variables for the deep learning classification model. The model was trained and evaluated using the same experimental procedure as Experiment 1.

This experimental design allows the classification performance of deep learning with and without feature selection to be compared directly. The manuscript describes these two trials explicitly: the first trial used deep learning alone, while the second used data selected using Weight by User Specification.

### 2.8 Model Evaluation

The performance of both models was evaluated using a confusion matrix. The confusion matrix consisted of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Classification accuracy was calculated using:

$$\textbf{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \times 100\%$$

Classification error was also calculated to determine the proportion of incorrectly classified
The concept flow in this research was carried out in accordance with the flowchart in Figure 1. The health insurance data that had been collected was checked for preprocessing so as not to interfere with accuracy. After the data is preprocessed, the data is divided into two, namely training data and testing data. After data sharing, two trials were carried out. The first trial was carried out using only the deep learning classification method, while the second trial used data that had been selected using the Weight by

User specification method. After both trials have been carried out, the next stage is to carry out an evaluation model using a confusion matrix to produce accuracy values. The accuracy value is then used for analysis using the T-test method.

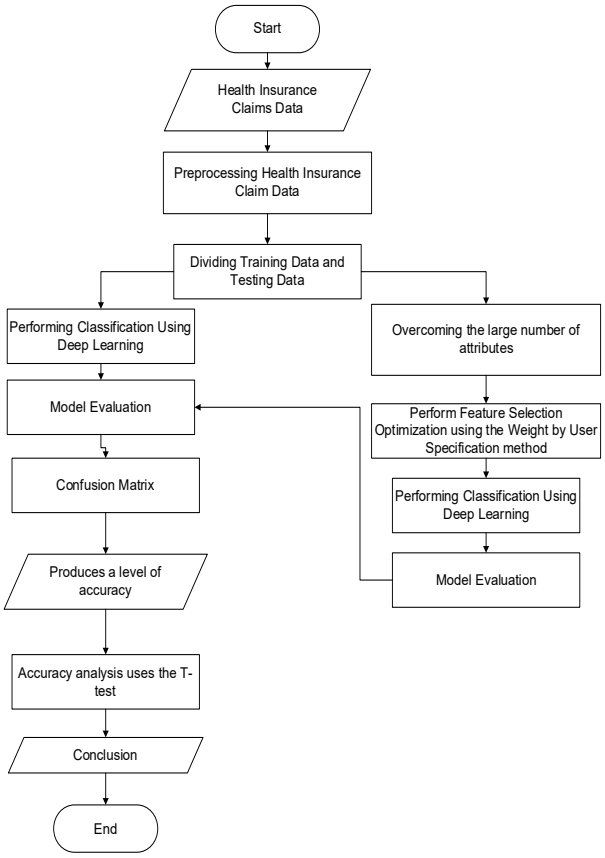



Figure 1. Flowchart system

# III. RESULTS AND DISCUSSION

Based on the results of deep learning modeling, produce model performance calculations by creating a confusion matrix, as shown in Table 4.

Table 4. Confusion Matrix Calculation Result Deep Learning Classifier

| | True Worthy | True Pending |
|---|---|---|
| **Pred. Worthy** | 2319 | 12 |
| **Pred. Pending** | 15 | 42 |

Based on the confusion matrix in Table 4, the deep learning model correctly classified 2,319 records as Worthy and 42 records as Pending. Therefore, the true positive (TP) is 2,319 and the true negative (TN) is 42. Meanwhile, 15 Pending records were incorrectly classified as Worthy, representing the false positive (FP), while 12 Worthy records were incorrectly classified as Pending, representing the false negative (FN). Thus, the confusion matrix consists of TP = 2,319, TN = 42, FP = 15, and FN = 12. Based on these results, the model achieved an accuracy of 98.87%, with a classification error of 1.13%. These results indicate that the deep learning model was able to classify BPJS Health insurance claims with a high level of accuracy, although a small number of records were still incorrectly classified.

Table 5. Confusion Matrix Calculation Results Classifier deep learning with feature selection Weight by User Specifications

| | True Worthy | True Pending |
|---|---|---|
| **Pred. Worthy** | 2327 | 12 |
| **Pred. Pending** | 7 | 42 |

Table 5 presents the confusion matrix obtained from the deep learning model combined with Weight by User Specification feature selection. The model correctly classified 2,327 Worthy records and 42 Pending records. Therefore, the true positive (TP) is 2,327 and the true negative (TN) is 42. In addition, 7 Pending records were incorrectly classified as Worthy, representing the false positive (FP), while 12 Worthy records were incorrectly classified as Pending, representing the false negative (FN). Thus, the confusion matrix consists of TP = 2,327, TN = 42, FP = 7, and FN = 12. Compared with the deep learning model without feature selection, the results indicate that the application of Weight by User Specification reduced the number of misclassified records and improved the overall classification performance.

The comparison between the two models shows that the integration of Weight by User Specification feature selection improved the classification performance of the deep learning model. The accuracy increased from 98.87% to 99.20%, representing an improvement of 0.33 percentage points. At the same time, the classification error decreased from 1.13% to 0.80%. The number of Pending records incorrectly classified as Worthy decreased from 15 to 7, while the number of Worthy records incorrectly classified as Pending remained at 12. These findings indicate that feature selection was able to reduce classification errors, particularly for the Pending class, while maintaining the correct classification of Worthy and Pending records. Therefore, the Weight by User Specification method contributed to improving the predictive performance of the deep learning model for BPJS Health insurance claim classification.

For the purpose of testing hypotheses regarding deep learning (DL) and deep learning models with

feature selection, various tests were conducted using method statistics User-Specified Weight (DL+FS)

$H_0$: There is no difference in the average accuracy value of DL and DL+FS.

$H_1$: There is a difference between the average accuracy value of DL and DL+FS

Table 6. Comparison of DL and DL+FS Accuracy

| | DL | DL+FS |
|---|---|---|
| **Accuracy** | 98.87 | 99.20 |
| **Classification Error** | 1.13 | 0.80 |

Following a comparison of the mark accuracy results from DL and DL+FS, the Paired Two-sample t-test for Means was used to analyze the data, with potential results shown in Table 7.

Table 7. Statistical Difference Test Results for DL and DL+FS Accuracy

| | DL | DL+FS |
|---|---|---|
| **Mean** | 50 | 50 |
| **Variance** | 4776.5538 | 4841.28 |
| **Observations** | 2 | 2 |
| **Pearson Correlation** | 1 | |
| **Hypothesized Mean Difference** | 0 | |
| **df** | 1 | |
| **t Stat** | -5.04647E-16 | |
| **P(T<=t) one-tailed** | **0.499999982** | |
| **t Critical one-tail** | 6.313751515 | |
| **P(T<=t) two-tailed** | 0.999999964 | |
| **t Critical two-tail** | 12.70620474 | |

In Table 7, it can be seen that the average value of the DL and DL+FS models is equal to 50. In the statistical difference test, the alpha value is determined at 0.05; if the p-value is smaller than the alpha value ($p < 0.05$), H0 is rejected, and H1 is accepted. If the alpha value ($p > 0.05$), then H0 is accepted, and H1 is rejected, so there is no significant difference between the compared models. Based on the experimental results, it was found that the p-value was 0.499999982, so it was accepted even though the accuracy results were not much different between the compared models. However, the DL and DL+FS models increased accuracy by 0.33 %.

# IV. CONCLUSION

The importance of insurance claims has a significant impact on various aspects of hospital operations, particularly those related to disease management. This impact includes the availability of medications, procurement of medical equipment, and the provision of incentives for employee performance. Effective insurance claim management enables hospitals to better prepare for operational needs and maintain the quality of healthcare services. Therefore, predicting health insurance claims can support hospitals in improving the efficiency of claim management and operational decision-making.

The classification system developed in this study applies a deep learning algorithm integrated with the Weight by User Specification feature selection method. The results show that the deep learning model without feature selection achieved an accuracy of 98.87%, while the integration of Weight by User Specification increased the accuracy to 99.20%. In addition, the classification error decreased from 1.13% to 0.80%. These findings indicate that feature selection can improve the classification performance of the deep learning model by reducing classification errors while maintaining a high level of prediction accuracy.

However, this study has several limitations. The analysis was conducted using BPJS Health insurance claim data from a single hospital, namely Kumala Siwi Hospital, and focused on the classification of Worthy and Pending claims. Therefore, the findings may not be directly generalizable to other hospitals with different claim characteristics, data distributions, or operational conditions. In addition, the study focused on the Weight by User Specification feature selection method combined with deep learning, so other feature selection techniques and classification algorithms were not evaluated in the same experimental setting.

For future research, the proposed approach should be validated using datasets from multiple hospitals and different periods to assess its generalizability and robustness. Further studies could also compare Weight by User Specification with other feature selection methods and evaluate alternative deep learning or machine learning algorithms. In addition, future research may investigate other performance metrics, such as precision, recall, F1-score, and the area under the ROC curve, to provide a more comprehensive evaluation, particularly for the identification of Pending claims. Such research could support the development of a more robust and generalizable BPJS Health insurance claim prediction framework for hospital decision-making.

# AUTHOR'S CONTRIBUTION

Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing: Authors.

## AVAILABILITY DATA AND MATERIALS

The dataset used can be accessed via the link.

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