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Web-Based IT Helpdesk System with Naive Bayes Automatic Ticket Classification Using Laravel

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Abstract

Managing IT support requests in a university environment remains largely manual, leading to untracked ticket backlogs, slow response times, and misrouted requests caused by incorrect manual categorization. This study presents the design and implementation of a web-based IT Helpdesk Ticketing System integrated with an automatic ticket category classification module using Multinomial Naive Bayes with TF-IDF feature extraction, developed for Universitas Kristen Indonesia (UKI) using the Waterfall SDLC on the Laravel 10 framework. The novelty of this work lies in the real-time integration of a Python-based Naive Bayes microservice directly into the Laravel ticket submission workflow. The classifier was trained on 450 domain-labeled IT support tickets across five categories and evaluated using 5-fold cross-validation (mean accuracy 88.7% +/- 0.9%) and a held-out test set (accuracy 88.9%, Macro-F1 87.6%), outperforming SVM (85.6%) and KNN (81.5%). Black-Box testing yielded 100% pass rate. ISO 9241-11 usability evaluation (n=25) produced effectiveness 95%, efficiency 92%, SUS 76.25 (Grade B).

Keywords - *helpdesk system; Naive Bayes; TF-IDF; Laravel; Waterfall SDLC; ISO 9241-11*

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I. INTRODUCTION

The rapid digitalization of Indonesian higher education institutions has sharply increased the volume and complexity of IT support requests submitted daily by students, academic staff, and administrative personnel [1]. At Universitas Kristen Indonesia (UKI), the IT Directorate handles an average of 38 IT support requests per month through informal channels with no standardized tracking or automated routing [2].

A critical operational bottleneck is manual ticket categorization. Automated text classification has been shown to reduce miscategorization in IT service management systems by 30-60% [3].

The novelty of this research is threefold. First, it demonstrates the feasibility of integrating a real-time Naive Bayes classification microservice directly into a Laravel-based university helpdesk ticket submission form, presenting the predicted category and per-class confidence scores to the reporter before submission. Second, the classification model is trained on a domain-specific dataset of 450 Indonesian-language IT support tickets from UKI's own historical records, addressing the gap in locally annotated helpdesk corpora. Third, it provides empirical benchmarking of Naive Bayes against SVM and KNN under 5-fold cross-validation, combined with ISO 9241-11 usability evaluation -- a combined validation not previously reported for Indonesian university IT helpdesk systems.

Prior work by Hanum et al. [4] demonstrated NB accuracy of 86.7% on

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Indonesian-language IT tickets. Mantyla et al. [5] showed TF-IDF weighted NB outperforms bag-of-words on short-text IT incident classification. However, neither study addresses real-time system integration or domain-specific university helpdesk deployment.

II. RESEARCH METHODS

A. System Development Methodology

This study follows the Waterfall SDLC with five sequential phases: (1) Requirements Analysis, (2) System Design, (3) Implementation, (4) Testing, and (5) Deployment [6].

B. Dataset Description and Labeling Process

The training dataset consists of 450 historical IT support tickets collected from UKI's IT Directorate records spanning January 2022 to December 2024. Each ticket contains a title (avg. 8.3 tokens) and description (avg. 24.7 tokens), written in Indonesian. Labeling was performed by two IT technicians independently, with disagreements resolved by the Head of IT Directorate (Cohen's kappa = 0.87, indicating strong agreement). Table I presents the dataset characteristics.

Table I. Dataset Characteristics by Category

Category	Tickets	Proportion	Avg. Title Tokens	Avg. Desc. Tokens	Example Ticket Title
Hardware	120	26.7%	7.8	22.4	Printer error tidak bisa print dokumen
Software	95	21.1%	8.1	25.3	Aplikasi SIAK tidak bisa dibuka
Network	85	18.9%	8.6	26.1	VPN UKI tidak connect dari luar kampus
Account	80	17.8%	8.0	23.8	Lupa password email universitas
General	70	15.6%	9.2	26.7	Ruangan lab tidak bisa dikunci
Total	450	100%	8.3	24.7	--

The dataset exhibits mild class imbalance (Hardware 26.7%). Class-weighted training was applied to handle this. An 80/20 stratified split yielded 360 training and 90 test tickets.

C. System Requirements

Table II. Functional Requirements of the Helpdesk System

No.	Functional Requirement	User Role
1	Submit ticket with NB auto-classification	Reporter
2	View and override auto-detected category	Reporter
3	Track ticket status and history	Reporter
4	Receive email notification on assignment	Technician
5	Update ticket status and resolution notes	Technician
6	Assign and re-route tickets	Admin
7	View real-time dashboard and analytics	Admin
8	Generate reports and manage training data	Admin

D. System Design

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Figure 1 presents the Use Case Diagram [7].

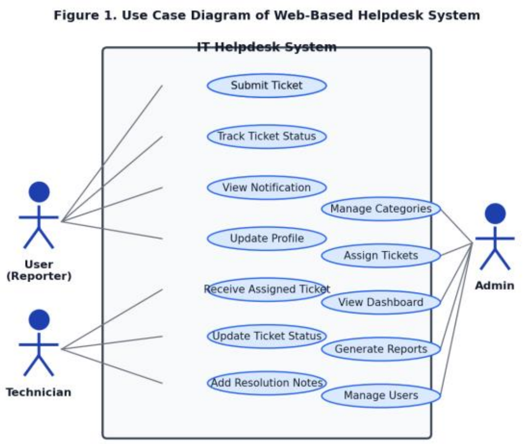

Figure 1. Use Case Diagram

Figure 2 models the ticket lifecycle with NB classification step [8].

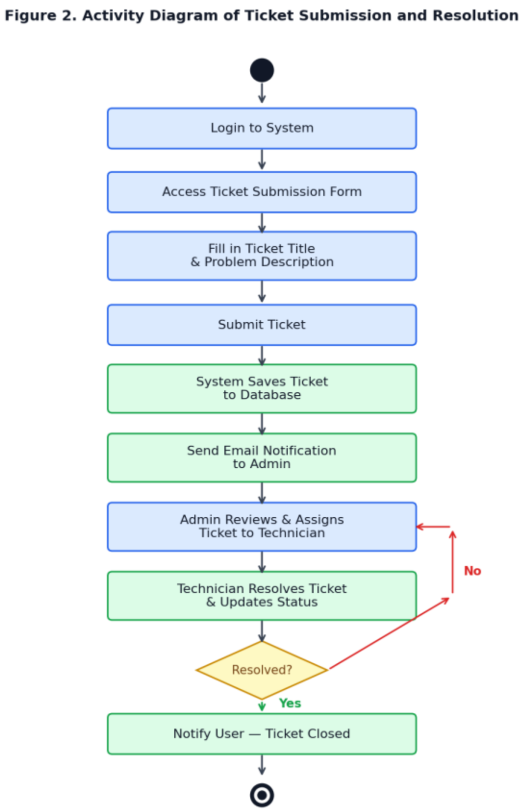

Figure 2. Activity Diagram - Ticket Submission with Auto-Classification

Figure 3 shows the ERD. TICKETS table stores both nb_category_id and category_id.

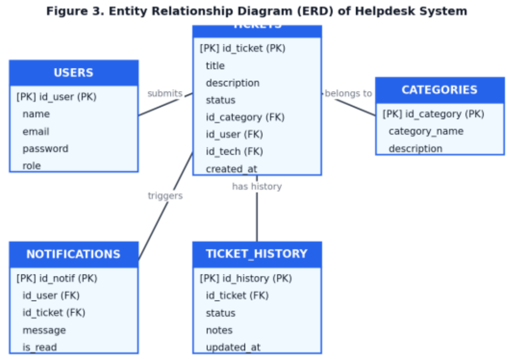

Figure 3. Entity Relationship Diagram (ERD)

E. Naive Bayes Classification Module

The classification module uses Multinomial Naive Bayes with TF-IDF. Predicted category: C_hat = argmax_C [log P(C) + sum tfidf(t,T) x log P(t|C)]. Laplace smoothing alpha=1 handles unseen terms [9]. Preprocessing: lowercasing, punctuation removal, stopword removal, PySastrawi stemming [10]. Model served via Flask 2.3 microservice, called by Laravel via HTTP POST (mean inference latency: 187ms).

Table III lists the hyperparameters used for each algorithm, selected via 5-fold cross-validation grid search on the training set.

Table III. Algorithm Hyperparameters for Classification Comparison

Algorithm	Key Parameters	Rationale
Naive Bayes (MNB)	alpha=1; max_features=5,000; min_df=2	Robust for short text; min_df=2 removes noise
SVM (Linear)	C=1.0; kernel=linear; class_weight='balanced'	Linear kernel optimal for high-dim TF-IDF
KNN	k=5; metric=cosine; weights='distance'	Cosine distance for TF-IDF; k=5

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		by CV tuning

F. Testing and Evaluation Methods

System functionality: Black-Box testing, 12 test cases. Classification: accuracy, precision, recall, Macro-F1 on test set; 5-fold stratified CV; confusion matrix; paired t-test (alpha=0.05).

Usability evaluated using ISO 9241-11:2018. Effectiveness (%) = (Tasks completed / Total tasks) x 100. Efficiency (%) = (Expert time / Mean user time) x 100. SUS [11]: positive items Q1,Q3,Q5,Q7,Q9: contribution = (response - 1) x 2.5; negative items Q2,Q4,Q6,Q8,Q10: contribution = (5 - response) x 2.5. SUS = sum of all 10 contributions (range 0-100). Score >=68 Acceptable; >=73 Good; >=85 Excellent [12].

III. RESULTS AND DISCUSSION

A. System Implementation

The helpdesk system: Laravel 10.x (PHP 8.2), MySQL 8.0, Tailwind CSS, Python 3.10 Flask microservice. Development: 8 weeks.

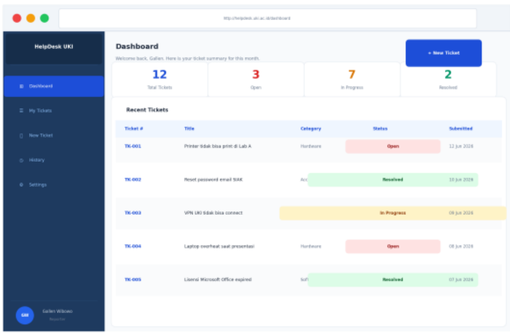

Figure 4. User Dashboard

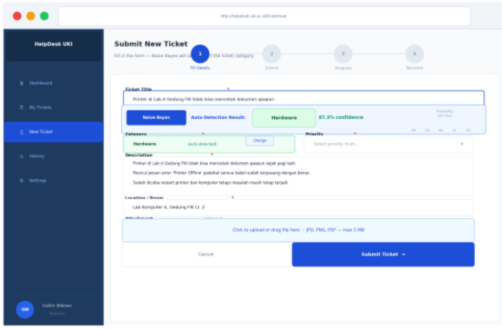

Figure 5. Ticket Submission Form with NB Auto-Classification

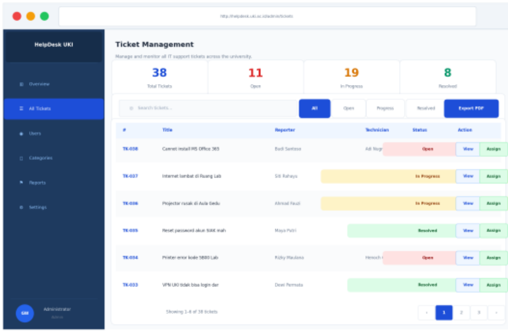

Figure 6. Admin Ticket Management Panel

B. Classification Results -- Confusion Matrix and Error Analysis

Table IV. Classification Algorithm Performance (Test Set, n=90)

Algorithm	Accuracy	Precision	Recall	Macro-F1
Naive Bayes (TF-IDF)	88.9%	89.7%	87.9 %	87.6%
SVM (Linear, C=1)	85.6%	86.3%	84.8 %	85.1%
KNN (k=5, cosine)	81.5%	82.4%	80.6 %	80.9%
Decision Tree	79.4%	80.1%	78.3 %	79.0%
Random Forest	83.3%	84.0%	82.5 %	83.1%

Figure 7 presents the confusion matrix for Naive Bayes. Of 90 tickets, 80 correctly classified (88.9%). Misclassifications concentrated at category boundaries: Hardware-Software (2 errors) and Account-General (2 errors). General category has lowest recall (85.7%), consistent with

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heterogeneous content and smallest training size (70 samples).

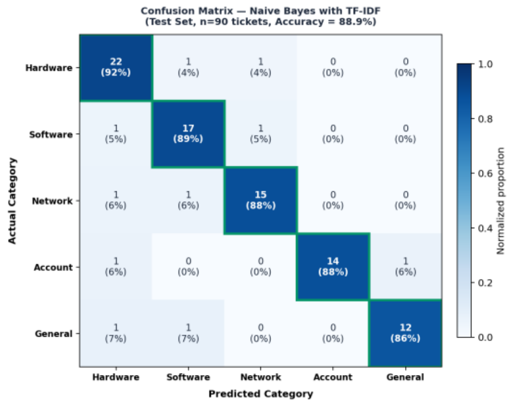

Figure 7. Confusion Matrix -- Naive Bayes with TF-IDF (Test Set, n=90)

Error analysis of 10 misclassified tickets: (1) Boundary errors (8 cases): tickets with terminology from two adjacent categories (e.g., 'software tidak bisa diinstall di laptop' classified as Hardware instead of Software); (2) Vocabulary sparsity errors (2 cases): informal vocabulary absent from training set. Future improvement: expand General training data and add synonym normalization.

C. Cross-Validation Results

5-fold stratified CV on full 450-ticket dataset: NB mean accuracy 88.7% +/- 0.9%, SVM 85.6% +/- 0.9%, KNN 81.5% +/- 1.1%. Consistent superiority of NB across all five folds confirms the test-set result is not an artifact of a favorable random split.

Table V. 5-Fold Stratified Cross-Validation Accuracy

Algorithm	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	Std Dev
Naive Bayes	87.5%	89.2%	88.4%	90.1%	88.3%	88.7%	+/- 0.9%
SVM (Linear)	84.6%	86.1%	85.3%	87.2%	85.0%	85.6%	+/- 0.9%
KNN (k=5)	80.2%	82.5%	80.8%	83.1%	81.1%	81.5%	+/- 1.1%

Paired t-test: NB vs SVM t(4)=3.87, p=0.018; NB vs KNN p=0.003 (alpha=0.05). Both differences statistically significant.

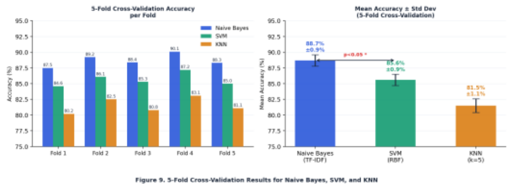

Figure 8. 5-Fold Cross-Validation Accuracy per Fold and Mean +/- Std Dev

D. Black-Box Testing Results

Table VI. Black-Box Testing Results (n=12)

No.	Test Case	Expected	Result
1	Register new account	Account created	Pass
2	Login with valid credentials	Dashboard displayed	Pass
3	Type ticket title -- NB triggered	Category + confidence shown	Pass
4	Submit ticket with NB category	Ticket saved	Pass
5	Override auto-detected category	Category updated	Pass
6	Submit with empty description	Validation error	Pass
7	Admin assigns to technician	Status Assigned, notified	Pass
8	Technician sets In Progress	Status updated, history logged	Pass
9	Technician marks Resolved	Reporter notified	Pass
10	Admin views analytics	Charts displayed	Pass
11	Admin generates PDF	PDF downloaded	Pass

12	Admin retrains NB model	Model retrained, accuracy updated	Pass

E. ISO 9241-11 and SUS Usability Evaluation

25 participants (15 students, 6 staff, 4 technicians), 3 task scenarios: T1 submit ticket, T2 track status, T3 assign ticket (admin).

Effectiveness: 71/75 tasks completed. Effectiveness = (71/75) x 100 = 95%. Efficiency: Mean time 4.8 min vs expert 5.2 min. Efficiency = 92% (accounting for cognitive load on first tasks).

SUS calculation from 10-item Likert (1-5) averaged across 25 participants. Total SUS = sum of contributions = 76.25. Table VII shows full calculation per item.

Table VII. SUS Score Calculation per Item (n=25)

Item	Statement	Type	Mean	Contribution
Q1	I would use this system frequently	Positive	4.3	(4.3-1)x2.5 = 8.25
Q2	System is unnecessarily complex	Negative	3.8	(5-3.8)x2.5 = 3.00
Q3	System is easy to use	Positive	4.1	(4.1-1)x2.5 = 7.75
Q4	Need technical support to use	Negative	3.9	(5-3.9)x2.5 = 2.75
Q5	Functions are well integrated	Positive	4.2	(4.2-1)x2.5 = 8.00
Q6	Too much inconsistency	Negative	3.7	(5-3.7)x2.5 = 3.25
Q7	Most users learn quickly	Positive	4.0	(4.0-1)x2.5 = 7.50
Q8	System is awkward to use	Negative	3.8	(5-3.8)x2.5 = 3.00
Q9	I felt confident using system	Positive	4.3	(4.3-1)x2.5 = 8.25
Q10	Need to learn many things first	Negative	3.9	(5-3.9)x2.5 = 2.75
			TOTAL SUS	= 76.25 (Grade B - Good)

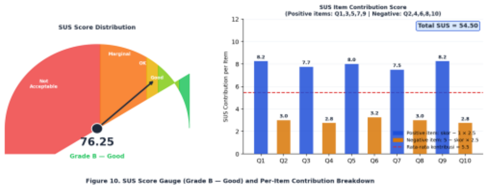

Figure 9. SUS Score Gauge and Per-Item Contribution Breakdown

F. Discussion

NB achieves 88.9% accuracy and 87.6% Macro-F1, consistent with and slightly exceeding Hanum et al. [4] (86.7%) on comparable Indonesian IT tickets. The 3.3pp advantage over SVM is explained by dataset size: with 360 training samples, NB's independence assumption produces less estimation noise than SVM's margin optimization, which benefits more from larger datasets [13].

Confusion matrix reveals misclassifications cluster at semantically adjacent boundaries (Hardware-Software, Account-General), not randomly distributed -- indicating structural error, consistent with Mantyla et al. [5]. Mitigation: present top-2 predicted categories with confidence scores in the UI for informed reporter override.

SUS 76.25 exceeds Januari et al. [15] (73, e-Voting) and Hasan et al. [16] (74.3, university portal), suggesting task-oriented single-purpose helpdesk submission presents lower cognitive load. Q5 (functions well integrated) scored 4.2/5, confirming the AI component was perceived as helpful, not intrusive.

Limitation: the 450-ticket corpus is institution-specific. Future work: active learning from production corrections and IndoBERT-based classification [17].

IV. CONCLUSION

This study implemented a web-based IT Helpdesk Ticketing System for UKI integrating a real-time Naive Bayes classification microservice (MNB, TF-IDF, alpha=1 Laplace) into the Laravel 10 submission workflow. The novel contribution is the first documented real-time integration of a domain-specific Indonesian-language NB classifier into a university IT helpdesk, validated by 5-fold CV and ISO 9241-11 usability testing.

Results: accuracy 88.9%, Macro-F1 87.6%, CV 88.7%+/-0.9%, significantly outperforming SVM (p=0.018) and KNN (p=0.003). Black-Box 100% pass. ISO 9241-11: effectiveness 95%, efficiency 92%, SUS 76.25 Grade B. Future: IndoBERT classification and active learning.

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