

Development of KabuTeach: a character-based decision support system for mushroom classification

Vilchor G. Perdido¹, Melinda A. Beninsig², Daniel Marvin B. Ramel³

¹Department of Computer Science, College of Information Technology Education, Nueva Vizcaya State University, Bayombong, Philippines

²College of Information Technology and Computer Science, University of the Cordilleras, Baguio City, Philippines

³Department of Natural Sciences, College of Arts and Sciences, Nueva Vizcaya State University, Bayombong, Philippines

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ABSTRACT

Mushroom misidentification remains a persistent public health risk in rural communities, causing poisoning and fatalities worldwide. This study presents KabuTeach, a web-based decision support system (DSS) for classifying mushrooms as edible or poisonous. The system is trained on the UCI mushroom dataset (8,124 instances, 22 categorical morphological attributes) using the categorical Naïve Bayes algorithm with Laplace smoothing ($\alpha=1.0$) through the Rubix ML framework. The system employed a hybrid interactive structure and event-driven architecture with the model-view-controller pattern, enabling real-time classification, human-in-the-loop expert validation, and SMS-based result delivery for low-connectivity rural environments. Model evaluation using a 70:30 holdout method achieved 99.63% accuracy, while 5-fold cross-validation yielded a mean accuracy of 99.66% ($\pm 0.1118\%$). Performance metrics, including a confusion matrix, per-fold results with standard deviations, precision, recall, F1-score, and specificity, confirm model robustness, attributed to the clean and discriminative categorical features of the dataset and the use of Laplace smoothing. Usability testing with 102 respondents using the USE questionnaire achieved a grand mean of 5.93 (agree). Reliance on the North American UCI dataset limits direct Philippine applicability; future work will focus on locally sourced, expert-labeled datasets. KabuTeach is a reliable, interpretable, and user-centered DSS that bridges traditional knowledge and modern ICT for safer rural mushroom foraging.

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Corresponding Author:

Vilchor G. Perdido

Department of Computer Science, College of Information Technology Education

Nueva Vizcaya State University

Bayombong, Nueva Vizcaya, Philippines

Email: vgperdido@nvsu.edu.ph

1. INTRODUCTION

Mushrooms are globally recognized for their nutritional and medicinal properties, providing calcium, phosphorus, vitamins, proteins, and antioxidants, and contributing to treatments for illnesses such as cancer and obesity [1]. However, mushroom consumption poses significant public health risks, as some species are poisonous and can cause severe illness or death when misidentified [2]. Between 1999 and 2016, the United States recorded over 133,700 mushroom poisoning cases, while Germany documented 22 fatalities from 2000 to 2018 [3]. In the Philippines, poisoning incidents remain prevalent, with recent cases in Kalinga, Benguet, and Mountain Province affecting dozens of individuals, including children [4]. In Northern

Luzon, particularly Nueva Vizcaya, mushroom foraging remains an important livelihood and food source for farmers, indigenous groups, and low-income households.

Mushroom identification in many rural communities across the Philippines largely depends on indigenous knowledge and morphological observation. Practices documented in Bicol Natural Park and Aeta settlements in Central Luzon show reliance on local terminology, preparation rituals, and generational knowledge [5], [6]. At the same time, folklore, such as the association of mushroom growth with lightning, is evident in Gaddang traditions [7]. Although culturally significant, these practices rely heavily on visible traits such as color, size, and shape, making them vulnerable to misidentification. Toxic species often resemble edible varieties [8], and immature or damaged specimens further reduce the reliability of morphological cues [9]. While molecular techniques such as DNA barcoding offer higher accuracy [8], [10], these methods remain impractical in rural settings. The challenge extends globally: Thailand records annual poisoning fatalities [11], the death cap mushroom accounts for a significant proportion of German mushroom deaths [12], and the China centers for disease control and prevention (CDC) reported 505 poisoning cases in 2023 involving 97 toxic species [13]. Some countries mitigate these risks through expert consultation services, such as free mycological evaluations in Italy [14]. These global and local scenarios emphasize the urgency of accurate, accessible, and field-usable classification tools.

Advances in digital technology and machine learning (ML) provide promising solutions. ML algorithms can analyze structured datasets, detect patterns, and generate accurate predictions without explicit programming [15]. Their applicability has been demonstrated across healthcare, agriculture, cybersecurity, and smart systems [16]–[20]. In mycology, character-based classification using morphological traits such as cap shape, gill attachment, and spore color has proven effective in distinguishing edible from poisonous mushrooms [21], [22]. Studies applying Naïve Bayes, K-nearest neighbors, and support vector machines to the UCI mushroom dataset have achieved high accuracy [23], [24], with Naïve Bayes showing robustness, interpretability, and efficiency for categorical data [25], [26]. Additional enhancements, such as feature augmentation, dimensionality reduction, and explainable frameworks, have further improved its performance [27], [28].

Beyond classification models, several mushroom-related decision support systems (DSS) have been developed: a mushroom diagnosis assistance system (MDAS) [29], a mobile DSS achieving 94.19% accuracy in Thailand [30], and internet of things (IoT)-enabled systems for smart mushroom farming [31]. However, these systems primarily focus on algorithmic performance or controlled environments and lack integration with real-world constraints such as limited connectivity, user accessibility, and expert validation. In the Philippine context, research on DSS integration remains limited, focusing largely on species documentation [5], [8], [9], with only a few exploring ML-based classification [32], [33], and existing systems lacking integrated decision support [34].

Unlike prior studies that primarily emphasize algorithmic performance, this study focuses on system-level innovation by developing a deployable and user-centered DSS. Specifically, KabuTeach introduces three key contributions beyond the classification engine: (1) a hybrid architectural framework combining interactive structure and event-driven architecture with the model-view-controller (MVC) pattern, enabling modular and maintainable system design; (2) an SMS-based decision support mechanism implemented via the Semaphore application programming interface (API), ensuring classification result delivery even in low-connectivity rural environments — a capability absent in comparable systems such as MDAS [29] or the Thailand mobile DSS [30]; and (3) a human-in-the-loop expert validation layer through the mushroom resources research and development center (MRRDC), where mycologists review and finalize ML-generated classifications before results are communicated to mushroom pickers, serving as a critical safety check against false negatives. These contributions extend beyond classification accuracy, emphasizing real-world applicability, accessibility, and safety in rural Philippine communities.

This study addresses the identified gap by developing KabuTeach, a character-based DSS for mushroom classification. The system integrates a Naïve Bayes classifier trained on the University of California (UCI) mushroom dataset within a hybrid architectural framework aligned with MVC and client-server patterns. Users can input morphological features such as cap shape, gill type, and habitat to obtain immediate classification results, which are further validated by experts. By bridging traditional knowledge and modern ICT, KabuTeach aims to promote safer mushroom foraging, reduce poisoning incidents, and support sustainable food practices in rural communities.

2. RESEARCH METHOD

This study adopted a structured methodology for the design, development, and evaluation of the KabuTeach DSS. The overall process was guided by the rapid application development (RAD) model, which allowed iterative prototyping and continuous user feedback, and was further complemented by the design

thinking process to ensure a user-centered solution. The methodology included data collection, preprocessing, model training, system architecture design, iterative prototyping, testing, deployment, and usability evaluation.

2.1. Research design

This study combined quantitative and developmental research designs. The quantitative approach measured system usability through structured surveys using the usefulness, satisfaction, and ease of use (USE) questionnaire tool [35], while the developmental approach focused on constructing a functional DSS powered by the Naïve Bayes algorithm, selected for its efficiency in handling categorical data and proven accuracy in mushroom classification [23].

2.2. Software development model

The study adopted the RAD model shown in Figure 1 as the primary software development methodology, emphasizing iterative prototyping, active user involvement, and faster delivery of functional systems [36]–[40]. The process began with quick design and requirement gathering, followed by cycles of prototyping, user testing, and refinement. Each cycle involved mushroom experts and trained pickers, whose feedback guided improvements in functionality and usability.

Along with RAD, this study applied the five stages of the design thinking framework, as illustrated in Figure 2, to ensure a user-centered and iterative development process [41], [42]. User insights from the empathize and define phases were translated into system requirements through interviews and surveys [43]. The Ideate and Prototype phases produced and refined solution concepts using use cases, wireframes, and functional modules [44], [45] built with Laravel, Bootstrap, and Rubix ML. System performance and usability were validated in the test stage.

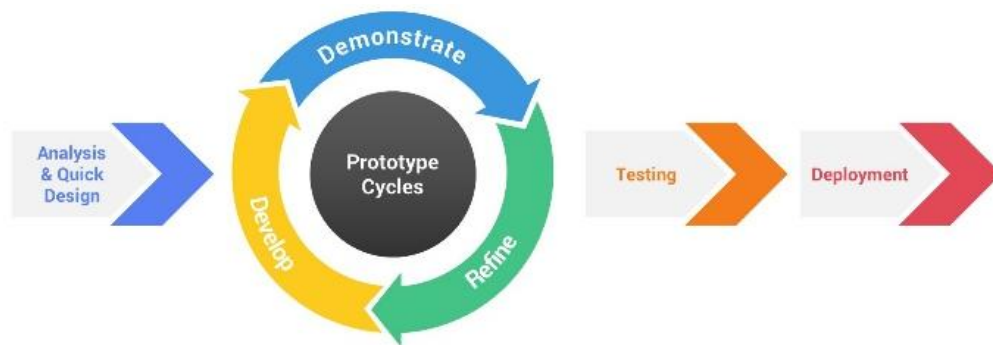


Figure 1. The RAD software development life cycle model

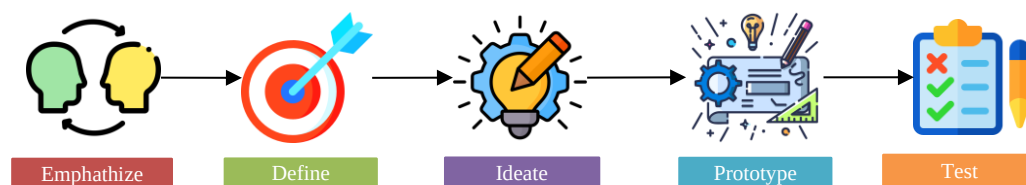


Figure 2. The five stages of the design thinking process framework

2.3. Data source and preprocessing

The study relied on the UCI mushroom dataset [46], accessed from Kaggle [47], consisting of 8,124 instances with 22 categorical morphological features, including cap shape, gill size, and spore print color. This dataset was pre-processed using Python in Jupyter Notebook, confirmed to have no missing values, and exhibited a balanced distribution of edible (52%) and poisonous (48%) classes. Since the Philippines does not yet provide a digital and ML-ready mushroom dataset, the morphological attributes were validated with the MRRDC of Nueva Vizcaya State University (NVSU) to confirm their relevance for the classification of locally foraged species.

It is acknowledged that the UCI mushroom dataset represents North American Agaricus and Lepiota families and may not fully capture the biodiversity of Philippine mushrooms. Field data in the Philippines may include noise, incomplete observations, and species variability not present in the benchmark dataset. To address this limitation, future work will focus on: (1) field data collection in collaboration with MRRDC to build a Philippine-specific annotated mushroom dataset; (2) expert-labeled sampling of endemic species from Nueva Vizcaya, Benguet, and Kalinga; and (3) model retraining or transfer learning using locally collected data to improve real-world classification accuracy.

2.4. ML model

The classification engine employed the categorical Naïve Bayes (NB) algorithm, selected for its efficiency in handling categorical datasets and suitability for large-scale classification tasks [23]. The model was implemented using the Rubix ML framework (v2.5) in PHP 8.2 within the Laravel 11 backend. Laplace smoothing ($\alpha = 1.0$) was applied to address zero-frequency issues, ensuring stable probability estimation when test samples contain feature values unseen during training [48]–[50].

Data partitioning was performed using stratified holdout methods across three configurations — 60:40, 70:30, and 80:20 — to evaluate the sensitivity of the classifier to varying training data sizes. The 70:30 split was selected as the primary holdout evaluation configuration, yielding 99.63% accuracy. Subsequently, 5-Fold Cross-Validation was applied to assess generalization, yielding a mean accuracy of 99.66% ($\pm 0.1118\%$). The 5-fold cross-validation result (99.66%) is adopted as the final reported performance metric, as cross-validation provides a statistically more robust generalization estimate than a single holdout test. Performance was assessed using Accuracy, Precision, Recall, Specificity, and F1-Score derived from confusion matrices [11], [22], [51].

2.4.1. Rubix ML implementation and hyperparameters

Figure 3 is a code snippet that illustrates the core training pipeline implemented in PHP using Rubix ML Library, while Table 1 indicates the key hyperparameters used by the KabuTeach Naïve Bayes classifier.

```
// Load categorical training samples and class labels
$dataset = new Labeled($samples, $labels);

// Initialize Categorical Naive Bayes with Laplace Smoothing ( $\alpha = 1.0$ )
$classifier = new NaiveBayes(null, 1.0);

// Train the classifier on the stratified labeled dataset
$classifier->train($dataset);

// Persist trained model to filesystem for production use
$storagePath = storage_path($pathname);
$model = new PersistentModel($classifier,
    new Filesystem($storagePath)
);
$model->save();
```

Figure 3. Core Rubix ML training pipeline code snippet for the KabuTeach Naive Bayes classifier

Table 1. Summary of the key hyperparameters of the KabuTeach Naïve Bayes classifier

Hyperparameter	Value	Description
Algorithm	Categorical Naïve Bayes	Appropriate for discrete categorical features
Laplace Smoothing (α)	1.0 (default)	Prevents zero probability for unseen feature values
Class Priors	null (estimated)	Computed from training set class distribution
Features Used	22 (all morphological)	No dimensionality reduction applied
Primary Data Split	Stratified 70:30 holdout	Preserves class ratio in train and test sets
Cross-Validation	Stratified 5-Fold	Proportional class distribution per fold
ML Library	Rubix ML v2.5	PHP-native ML library
Backend Framework	Laravel 11 / PHP 8.2	Web application backend runtime

2.5. System design and prototyping

KabuTeach was designed using a hybrid architectural framework integrating interactive structure architecture and event-driven architecture styles, along with the MVC pattern, as shown in Figure 4. The

interactive structure component ensured continuous engagement between users and the classifier engine, while the event-driven component handled asynchronous messaging through an SMS gateway, a critical design choice for rural areas with unreliable internet connectivity. The MVC pattern enforced modularity: the Model managed data and ML classification, the View delivered the user interface, and the Controller coordinated data flow, simplifying testing and iterative prototyping [52], [53].

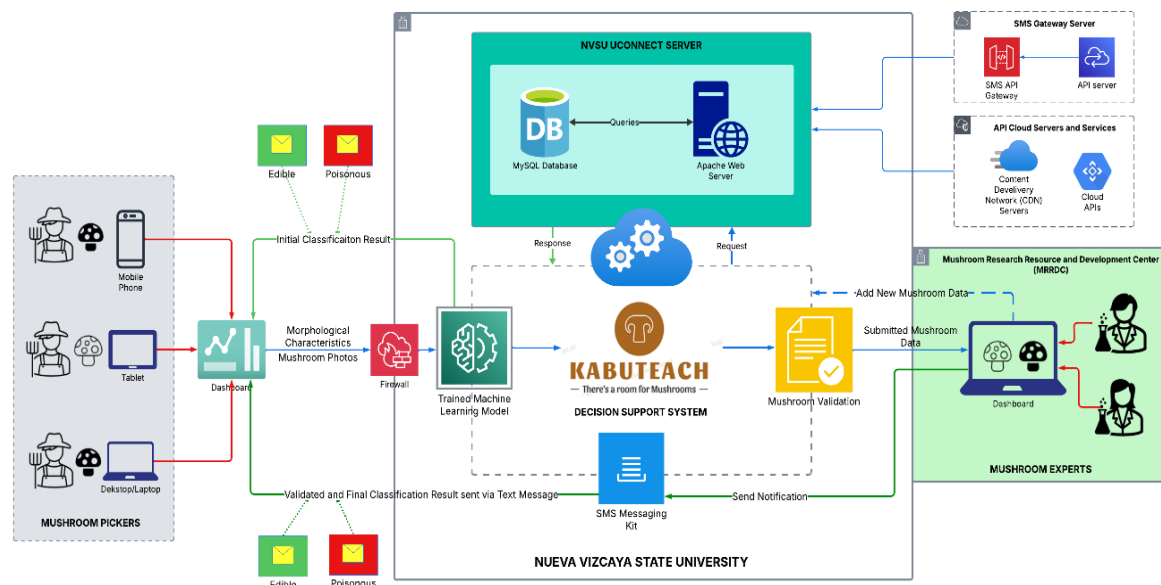


Figure 4. Hybrid architectural framework of the KabuTeach DSS

2.6. Testing and usability evaluation

Testing was conducted in three levels: unit, integration, and system testing. Accuracy testing used different train-test splits and cross-validation to measure classifier performance, with confusion matrix results computed to derive evaluation metrics [11], [51]. Usability testing employed the USE questionnaire tool with a 7-point Likert scale [35], [54].

The usability evaluation involved 102 respondents, comprising mushroom pickers and MRRDC experts, the two primary user groups of KabuTeach. This sample size is consistent with established usability research guidelines, which recommend 20-40 participants as a practical minimum for summative usability studies aimed at obtaining statistically stable results [55], [56]. Furthermore, Nielsen [57] demonstrated that testing with a sufficient number of representative domain users ensures comprehensive identification of usability issues. The deliberate focus on domain-specific stakeholders ensures ecological validity, as using actual intended users rather than general participants produces results that more accurately predict real-world performance [58]. Nonetheless, expanding future evaluations to include broader groups such as agricultural extension workers and public health officers is recommended to further strengthen generalizability.

2.7. System deployment

The final version of KabuTeach was deployed at the NVSU data center using a combination of layered and client-server deployment patterns. The layered architecture organized the system into three tiers: the presentation layer (user dashboards), the application layer (business logic, classification engine, and SMS notification services), and the data layer (relational database for user accounts, classification records, and validation logs). The client-server architecture facilitated real-time communication between clients and the NVSU server [39], [40].

3. RESULTS AND DISCUSSION

The development and evaluation of KabuTeach was grounded in systematic identification of its information and technological requirements, design of its core features, and rigorous assessment of its performance and usability. These findings are discussed in relation to existing literature and system design best practices.

3.1. Information and technological requirements

3.1.1. Data requirements

The study adopted the UCI mushroom dataset obtained from Kaggle [47], consisting of 8,124 instances and 22 categorical attributes. This dataset was pre-processed, confirmed to have no missing values, and exhibited a balanced distribution between edible (52%) and poisonous (48%) classes, justifying its selection over incomplete local datasets and ensuring reliable training for the Naïve Bayes algorithm [22]. Key morphological attributes such as cap color, gill size, odor, and bruises served as the primary features for classification. While the UCI mushroom dataset provides a clean and balanced benchmark, it does not fully capture the biodiversity of Philippine mushrooms. To address this, future work will involve the collection of locally sourced, expert-labeled mushroom datasets through MRRDC, enabling model retraining and validation in real-world Philippine conditions.

3.1.2. Hardware and software requirements

The system was deployed on the uConnect server at the NVSU Data Center, which provides a robust infrastructure equipped with a 16-core Xeon processor, 25 GB clustered RAM, and both HDD and SSD storage capacities. On the client side, mushroom pickers and experts accessed the system through internet-enabled devices such as smartphones, tablets, or computers. These specifications were essential to guarantee fast responses and lightweight performance even in rural areas, aligning with ICT best practices in user-centered DSS design [59], [60]. The design of the system prioritized accessibility for end-users, requiring only standard, widely available hardware. The hardware requirements for computer or desktop and mobile users are detailed in Table 2.

Table 2. End-user hardware and connectivity requirements for mobile and desktop users

Mobile		Desktop users	
Hardware component	Specifications	Hardware component	Specifications
CPU or processor	Dual-core 2.0 GHz or higher	CPU or processor	Quad-core 2.0 GHz or higher
RAM	4 GB RAM or higher	RAM	Minimum of 8 GB or higher
Internal storage capacity	Minimum of 8 GB or higher, with at least 500 MB free	Storage	Minimum 20 GB of available space or higher
Display	5.0-inch screen with 720p (1280 x 720) resolution or higher	Display	1280 x 800 resolution or higher
Connectivity	Internet Access (3G/4G LTE/5G/Wi-Fi) and Active Mobile Service	Connectivity	Broadband internet with 5 Mbps minimum speed or higher
SMS capability	The device must support basic SMS functionality	Graphics	Integrated or dedicated graphics are sufficient for web-based applications
Sensors	Camera and GPS support	Sensors	Location service or GPS support

On the other hand, the system was developed using various tools specified in Table 3. Its codebase was mainly built using Laravel 11 web framework (backend), MariaDB/MySQL (database), Bootstrap 5 (frontend), and Rubix ML library for ML integration. Crucial third-party integrations include the Semaphore API for SMS notifications and the MapBox Geocoding API with Leaflet for handling location data and map tiles. Functionally, the system must support mushroom data collection, initial classification, expert validation, and notification of results using SMS, while also meeting non-functional requirements for security and responsiveness. These tools ensured scalability and sustainability within the infrastructure of the university. The use of RAD and design thinking methodology, supported by these tools, contributed to efficient prototyping and high usability [61], [62].

Table 3. Software specifications used during the development of KabuTeach DSS

Software component	Specifications
Backend framework	Laravel 11.9
Frontend framework	Bootstrap 5.3
ML Library	Rubix ML 2.5
Runtime libraries	HTML5, CSS3, SweetAlert 2 (alert messages), JQuery 3.7.1, Croppie 2.6.5, Dropzone 5.9.3
API	Mapbox v3.10.0, Leaflet 2.0 (map tiles services), Semaphore (SMS Gateway)
Text or code editor	Microsoft Visual Studio Code version 1.99.3
XAMPP	Apache 2.4 (localhost server), PHP 8.2, MariaDB 10.4
Web browser	Brave Browser 1.77.95, Mozilla Firefox 137.0, Microsoft Edge 135.0

3.2. Features of the developed system

KabuTeach provides distinct interfaces and functionalities for its two key user groups: mushroom pickers and experts. It integrates modules for account registration, classification model training, profiling and classification, expert validation, and a mushroom foraging map.

Account registration used OTP-based SMS verification for pickers, while experts registered using NVSU uConnect email addresses. The classification model management (CMM) feature allows experts to upload the preprocessed dataset, perform stratified data splitting, and tune the NB model using K-fold cross-validation, generating the final NB model in .model format. The mushroom profiling and classification feature of KabuTeach is presented in Figure 5. Specifically, Figure 5(a) shows the selection of 22 predefined morphological characteristics, while Figure 5(b) illustrates the option for users to upload up to 10 sample photos of the collected mushrooms. Upon submission, the system provides an immediate initial classification and sends an SMS acknowledgment, which is particularly important for low-connectivity rural environments.

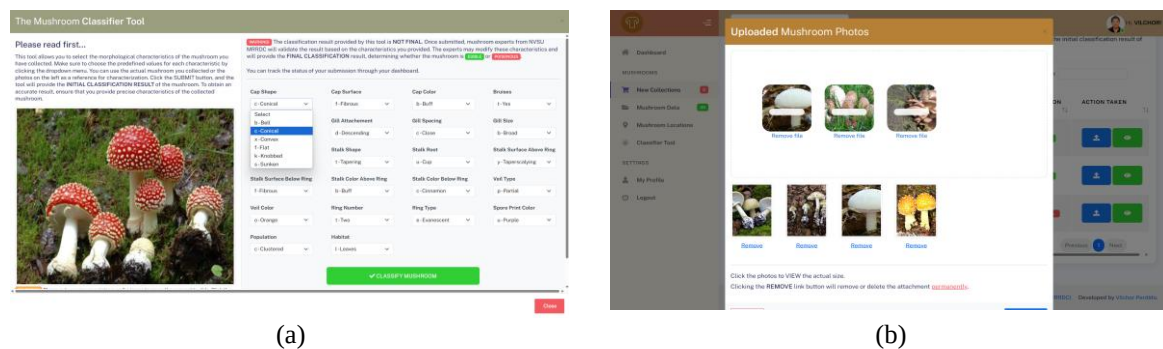


Figure 5. The KabuTeach DSS allows mushroom pickers to select and submit (a) morphological characteristics and (b) high-quality photos of collected mushrooms

The expert validation and result notification process in KabuTeach is presented in Figure 6. Specifically, Figure 6(a) shows the validation module used by MRRDC mycologists to review and finalize the ML-generated classification before result dissemination, implementing a human-in-the-loop safety mechanism that mitigates the risk of false negatives. Figure 6(b) shows the SMS text message through which the validated results are communicated to mushroom pickers. This expert validation layer is analogous to the free mycological evaluation services offered in Italy [14], adapted for the Philippine rural context through SMS delivery. The public mushroom foraging map in Figure 7 utilized Leaflet to display expert-validated mushroom finds using distinct green (edible) and red (poisonous) markers, promoting community awareness of safe foraging locations.

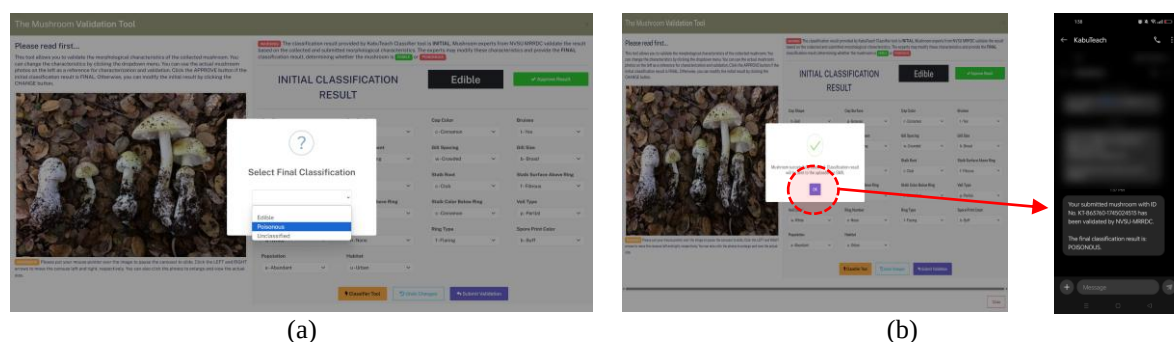


Figure 6. Mushroom experts validate submitted mushrooms using the (a) validation module, and results will be sent to mushroom pickers through (b) SMS text message

3.3. System performance and usability test

The proponents carried out two types of evaluations: (a) the performance test of the classification model, and (b) the overall usability test of KabuTeach. The outcomes of these evaluations provided valuable

insights into both the technical performance of the classification model and the practical usability of the system, forming the basis for assessing effectiveness of KabuTeach as a reliable decision support tool.

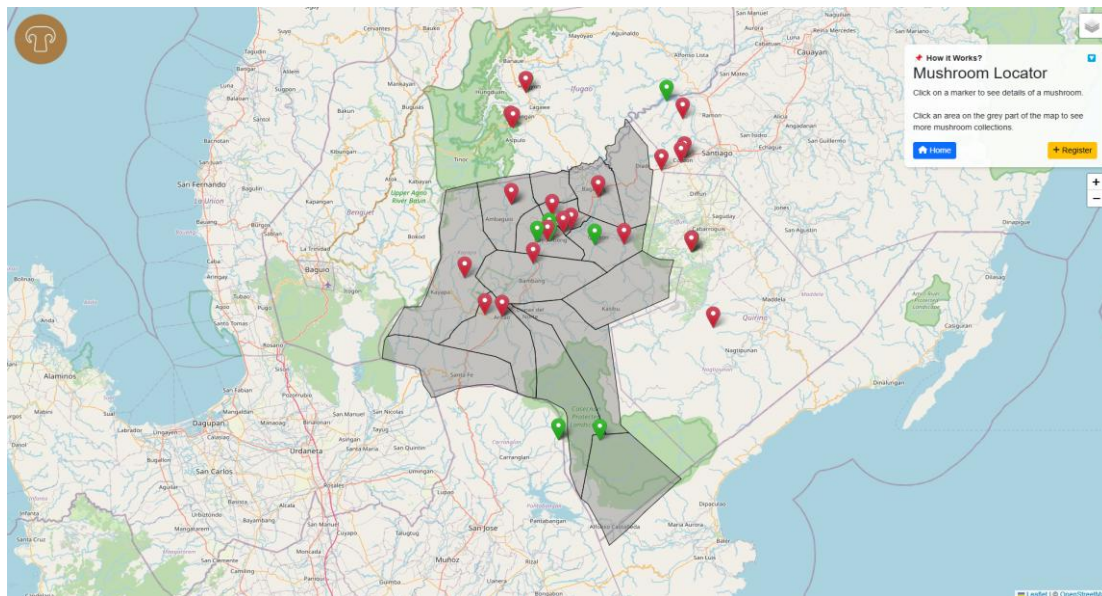


Figure 7. The mushroom foraging map showing validated mushrooms by MRRDC experts

3.3.1. Classification model performance

The performance of the KabuTeach classification model was evaluated using both a holdout validation method and a 5-Fold cross-validation approach to ensure reliability and generalizability. The holdout test utilized a 70:30 train-test split, while cross-validation provided a more robust assessment across multiple data partitions.

For the holdout test, the model was trained on approximately 5,687 instances (70%) of the dataset, while the remaining 30% (approximately 2,437 instances) were used for testing. The results of the holdout evaluation of the KabuTeach classification model are presented in Figure 8. Specifically, Figure 8(a) shows the confusion matrix used to evaluate the model's classification performance, while Figure 8(b) presents the corresponding performance metrics. The model achieved an accuracy of 99.63%.

Notably, 4 false negatives were observed, which were poisonous mushrooms incorrectly classified as edible. While this represents only 0.16% of the test set, it underscores the critical importance of the expert validation layer in KabuTeach, which provides a human safety check before classification results are communicated to mushroom pickers.

Predicted \ Actual	Edible (Actual)	Poisonous (Actual)
Predicted Edible	1257	4
Predicted Poisonous	5	1171

(a)

Metric	Value	Description
Accuracy	99.63%	Overall correct predictions
Precision	99.57%	Of predicted poisonous, how many were actually poisonous
Recall (Sensitivity)	99.66%	Of actual poisonous, how many were correctly detected
Specificity	99.6%	Of actual edible, how many were correctly identified
F1 Score	99.62%	Balance between precision and recall

(b)

(a)

(b)

Figure 8. The accuracy of the model was evaluated using (a) confusion matrix and (b) different performance metrics

To further validate the model, 5-fold cross-validation was conducted, and the results are presented in Figure 9. Specifically, Figure 9(a) shows the aggregated confusion matrix, while Figure 9(b) presents the fold-wise performance metrics and standard deviations across all evaluation metrics.

PREDICTED \ ACTUAL	EDIBLE (ACTUAL)	POISONOUS (ACTUAL)
Predicted Edible	4186	6
Predicted Poisonous	22	3910

(a)

FOLD	ACCURACY	PRECISION	RECALL	SPECIFICITY	F1 SCORE
Fold 1	99.57%	99.12%	100%	99.17%	99.56%
Fold 2	99.75%	99.49%	100%	99.52%	99.75%
Fold 3	99.75%	99.62%	99.87%	99.64%	99.74%
Fold 4	99.69%	99.74%	99.62%	99.76%	99.68%
Fold 5	99.51%	99.24%	99.74%	99.29%	99.49%
MEAN	99.66%	99.44%	99.85%	99.48%	99.64%
STD DEVIATION	0.1118%	0.2614%	0.1665%	0.2464%	0.1153%

(b)

Figure 9. The hypertuned model showing the overall (a) full confusion matrix and (b) performance metrics with standard deviations per-fold results across all metrics

The results demonstrate consistently high performance across all folds, with a low standard deviation of $\pm 0.1118\%$ for accuracy, indicating strong model stability and generalization capability. The mean accuracy of 99.66% exceeds several prior studies reporting approximately 89%–95% for Naïve Bayes on the same UCI dataset [23], [27]. Three factors account for this difference. First, prior studies reporting lower accuracy, notably 90.21% [23], used Gaussian Naïve Bayes, which is designed for continuous numerical features and represents a methodological mismatch for an entirely categorical dataset. KabuTeach uses Categorical Naïve Bayes, the appropriate variant for discrete feature values [48]. Second, the application of Laplace smoothing ($\alpha = 1.0$) eliminates zero-probability errors caused by unseen feature combinations in the test set, which directly improves classification accuracy over unsmoothed implementations [48]–[50]. Third, the UCI mushroom dataset is a well-curated, balanced, and noise-free benchmark with highly discriminative categorical features, particularly odor, that enable strong class separation even with simpler probabilistic classifiers [46]. The very low standard deviation across all five folds ($\pm 0.1118\%$) confirms that the result is stable and not a product of favorable data partitioning.

It is important to clarify the difference between the results reported in this study and those presented in the previous work of the lead author, where an accuracy of 89.13% was obtained using the same UCI mushroom dataset. The earlier implementation was developed using core PHP without a dedicated machine learning framework and employed a fixed 70:30 holdout validation with limited preprocessing and manual probability computations. In contrast, the present study utilizes Rubix ML v2.5, improved stratified preprocessing, consistent categorical encoding, explicit Laplace smoothing ($\alpha = 1.0$), and a more rigorous 5-Fold Cross-Validation evaluation strategy. These methodological enhancements resulted in higher and more stable performance. The two studies, therefore, represent different experimental implementations and evaluation strategies rather than conflicting results. The current manuscript is not a duplicate submission; the prior work is cited to establish the developmental trajectory of KabuTeach. To contextualize the performance of KabuTeach, Table 4 presents a comparison with related studies on mushroom classification.

Table 4. Comparison of KabuTeach with related mushroom classification studies

Study	Algorithm	Dataset	Accuracy
KabuTeach (this study)	Categorical NB + Laplace ($\alpha=1.0$)	UCI mushroom	99.66%
Sulistianingsih and Martono [24]	Ensemble (RF, stacking)	UCI mushroom	99%+
Vijayalakshmi and Ebenezer [63]	Random forest	UCI mushroom	98.1%
Ahmed <i>et al.</i> [64]	Decision tree/KNN/RF	UCI mushroom	100%
Ahmed <i>et al.</i> [64]	Naïve Bayes (no smoothing)	UCI mushroom	93%
Rianasari <i>et al.</i> [27]	Naïve Bayes + PCA	UCI mushroom	~95%
Hamonangan <i>et al.</i> [23]	Gaussian Naïve Bayes	UCI mushroom	90.21%
Dell'Era <i>et al.</i> [61]	CNN (deep learning)	Image-based	99.08%–99.5%
Rösch <i>et al.</i> [62]	Deep learning	Image-based	~99%

While CNN and ensemble methods achieve comparable or higher accuracy on image-based or multi-modal datasets, they require significantly greater computational resources, specialized hardware (e.g., GPUs), and large labeled image datasets, impractical for rural deployment in low-connectivity environments. KabuTeach's Categorical Naïve Bayes classifier achieves 99.66% with minimal computational overhead, making it the most appropriate algorithm for the design constraints of the system. Furthermore, character-based morphological classification is more interpretable and actionable for non-expert users than black-box CNN predictions, aligning with the safety-critical decision support purpose of the system.

Despite the strong results, it is important to note that such performance may not directly translate to real-world Philippine conditions, where field data may include noise, incomplete observations, and environmental variability not captured by the UCI benchmark dataset. To address this, KabuTeach incorporates a human-in-the-loop expert validation mechanism through the MRRDC, and future work will focus on collecting locally sourced, expert-labeled datasets to further enhance real-world applicability.

3.3.2. Usability test of KabuTeach

The usability of the KabuTeach DSS was assessed by 102 respondents comprising mushroom pickers and MRRDC experts, the two primary user groups of the system, using USE questionnaire. The instrument evaluated four dimensions using 30 items rated on a 7-point Likert scale, providing a robust measure of end-users' subjective perception of the system [38]. The qualitative interpretation of the mean scores is presented in Table 5.

Table 5. Qualitative interpretation of 7-point Likert scale measurements

Rating scale	Mean score interval	Descriptive rating
1	1.00 – 1.85	Strongly disagree (SD)
2	1.86 – 2.71	Disagree (D)
3	2.72 – 3.57	Slightly disagree (SLD)
4	3.58 – 4.43	Neither agree nor disagree (NAD)
5	4.44 – 5.29	Slightly agree (SLA)
6	5.30 – 6.15	Agree (A)
7	6.16 – 7.00	Strongly agree (SA)

a. Usefulness dimension

The usefulness dimension achieved a mean score of 5.87, interpreted as “Agree,” as shown in Table 6. This result indicates that respondents generally agreed that KabuTeach is a practical and effective tool that supports their mushroom classification tasks. The highest-rated item was “It is useful” (6.16, Strongly Agree), reflecting strong endorsement of the core purpose of the system. Items related to effectiveness (5.95), time-saving (5.92), and productivity (5.85) also received solid agreement. The slightly lower scores for “it gives me more control over the activities in my life” (5.70) and “it meets my needs” (5.71) suggest that while the system is considered useful, some respondents felt it partially meets their specific foraging decision-making needs, a finding consistent with open-ended feedback indicating that some morphological classification options did not include a “None” response, limiting input flexibility for certain real-world mushroom specimens.

Table 6. Mean scores of the usefulness dimension (n = 102)

Item description	Mean score	Descriptive rating
1. It helps me be more effective.	5.95	Agree
2. It helps me be more productive.	5.85	Agree
3. It is useful.	6.16	Strongly agree
4. It gives me more control over the activities in my life.	5.70	Agree
5. It makes the things I want to accomplish easier to get done.	5.84	Agree
6. It saves me time when I use it.	5.92	Agree
7. It meets my needs.	5.71	Agree
8. It does everything I would expect it to do.	5.82	Agree
Mean Score	5.87	Agree

b. Ease of use dimension

The ease of use dimension recorded a mean score of 5.75, interpreted as “Agree,” as presented in Table 7. Respondents agreed that KabuTeach is generally easy to use, simple (6.05), and user-friendly (6.03), with both occasional and regular users expected to find it agreeable (5.94). Items involving quick error

recovery (5.92) and consistent behavior (5.75) received agreement, suggesting a stable and navigable interface. Notably, Item 12, “It requires the fewest steps possible to accomplish what I want to do with it”, received the lowest rating across all 30 items (4.42, Neither Agree Nor Disagree), consistent with open-ended feedback indicating that the mushroom submission and classification workflow involves multiple steps, which some users, particularly first-time foragers, found slightly cumbersome. This result highlights an area for future interface optimization.

Table 7. Mean scores of the ease of use dimension (n = 102)

Item description	Mean score	Descriptive rating
9. It is easy to use.	6.05	Agree
10. It is simple to use.	6.05	Agree
11. It is user-friendly.	6.03	Agree
12. It requires the fewest steps possible to accomplish what I want to do with it.	4.42	Neither agree nor disagree
13. It is flexible.	5.84	Agree
14. Using it is effortless.	5.71	Agree
15. I can use it without written instructions.	5.77	Agree
16. I don't notice any inconsistencies as I use it.	5.75	Agree
17. Both occasional and regular users would like it.	5.94	Agree
18. I can recover from mistakes quickly and easily.	5.92	Agree
19. I can use it successfully every time.	5.82	Agree
Mean Score	5.75	Agree

c. Ease of learning dimension

The ease of learning dimension garnered the highest mean score of 6.16, interpreted as “Strongly Agree,” as shown in Table 8. This dimension outperformed all others, indicating that users found KabuTeach exceptionally intuitive and easy to master. The highest-rated item was “It is easy to learn to use it” (6.25, Strongly Agree), followed closely by “I learned to use it quickly” (6.23) and “I easily remember how to use it” (6.20). These results confirm that the interface of the system, workflow, and layout require minimal cognitive load, allowing users, including mushroom pickers with limited digital literacy, to achieve proficiency with little to no formal training. Open-ended feedback supported this finding, with respondents frequently citing “easy to use,” “user-friendly,” and “the design is very simple, which is good for beginners” as positive aspects. The slightly lower score for “I quickly became skillful with it” (5.99, Agree) suggests that while learning is fast, developing full proficiency requires some exploration of the features of the system.

Table 8. Mean scores of the ease of learning dimension (n = 102)

Item description	Mean score	Descriptive rating
20. I learned to use it quickly.	6.23	Strongly agree
21. I easily remember how to use it.	6.20	Strongly agree
22. It is easy to learn to use it.	6.25	Strongly agree
23. I quickly became skillful with it.	5.99	Agree
Mean Score	6.16	Strongly agree

d. Satisfaction dimension

The satisfaction dimension achieved a mean score of 5.95, interpreted as “Agree,” as indicated in Table 9. Users expressed overall contentment with the system, with “I am satisfied with it” (6.06) and “I would recommend it to a friend” (6.04) earning the highest scores within this dimension, reflecting a generally positive emotional response toward KabuTeach. Items related to enjoyment (6.02) and pleasantness (5.94) also received agreement, affirming a rewarding user experience. The lower scores for “I feel I need to have it” (5.75) and “it works the way I want it to work” (5.87) indicate that while users are satisfied, perceived necessity and behavioral alignment with user expectations have room for improvement, a finding echoed in open-ended feedback where several respondents noted that terminology used in mushroom characteristic selection was unfamiliar, occasional system errors were experienced, and connectivity limitations affected performance in some rural areas.

e. Summary of usability evaluation

The overall summary of the usability evaluation, presented in Table 10, shows a grand mean of 5.93, interpreted as “Agree.” This result indicates that 102 respondents consistently perceived KabuTeach as a usable and practical system across all four dimensions.

Table 9. Mean scores of the satisfaction dimension (n = 102)

Item description	Mean score	Descriptive rating
24. I am satisfied with it.	6.06	Agree
25. I would recommend it to a friend.	6.04	Agree
26. It is fun to use.	6.02	Agree
27. It works the way I want it to work.	5.87	Agree
28. It is wonderful.	5.99	Agree
29. I feel I need to have it.	5.75	Agree
30. It is pleasant to use.	5.94	Agree
Mean Score	5.95	Agree

Table 10. Overall result of the usability test across four dimensions (n = 102)

Dimension	Mean score	Descriptive rating
Usefulness	5.87	Agree (A)
Ease of Use	5.75	Agree (A)
Ease of Learning	6.16	Strongly Agree (SA)
Satisfaction	5.95	Agree (A)
Grand mean	5.93	Agree (A)

Ease of learning (6.16, strongly agree) emerged as the highest-rated dimension, confirming that KabuTeach is exceptionally intuitive and can be adopted quickly by users with varying levels of digital literacy, a critical requirement for a DSS deployed in rural foraging communities. Satisfaction (5.95, Agree) and Usefulness (5.87, Agree) both received solid agreement, affirming that users found the system rewarding and practically beneficial for mushroom classification tasks. Ease of use (5.75, Agree) received the lowest overall score among the four dimensions, largely influenced by the low rating on Item 12 (“Fewest steps possible”: 4.42), which reflects the multi-step nature of the mushroom submission workflow and highlights a priority area for future interface refinement.

The open-ended qualitative feedback from respondents reinforced the quantitative findings. Frequently cited positive aspects included the ease of use, user-friendly design, ability to classify mushrooms as edible or poisonous, and the helpfulness of the SMS notification and foraging map features of the system. Recurring areas for improvement included the absence of a “None” option in morphological classification inputs, unfamiliar mushroom terminology that challenged non-expert users, occasional performance and connectivity issues in low-connectivity rural areas, and a desire for more detailed mushroom information beyond classification results. These findings provide actionable directions for the next development iteration of KabuTeach.

Overall, the usability evaluation confirms that KabuTeach successfully meets the needs of its intended users and is well-positioned for broader community deployment. The Grand Mean of 5.93 (“Agree”) across 102 respondents reflects a robust and representative assessment of system usability, with ease of learning emerging as the strongest usability attribute of the system and ease of use presenting the most opportunity for continued improvement.

4. CONCLUSION

This study concludes that KabuTeach is a highly reliable, user-centered, and technically robust DSS for mushroom classification. Built using a hybrid Interactive Structure and Event-Driven Architecture and implemented through the MVC pattern, the system demonstrated strong performance grounded in well-defined technological requirements and the use of a clean, balanced mushroom dataset from the UCI machine learning repository.

The categorical Naïve Bayes classifier with Laplace smoothing ($\alpha = 1.0$) achieved 99.63% accuracy using the 70:30 holdout method and 99.66% using 5-fold cross-validation, with a low standard deviation of $\pm 0.1118\%$ across folds, confirming its suitability as a computationally efficient and highly generalizable model for safety-critical classification in rural settings. The superior accuracy relative to prior studies is attributable to the use of the appropriate categorical Naïve Bayes variant for discrete features, the application of Laplace smoothing, stratified data splitting, and the rigorous Rubix ML framework implementation, distinct methodological improvements over the earlier work of the lead author. The per-fold results and full confusion matrix confirm model stability and the presence of only 4 false negatives (0.16%), which are safeguarded by the expert validation layer.

System modules, including OTP-secured registration, structured morphological profiling, expert validation by MRRDC mycologists, SMS-based result delivery in low-connectivity areas, and a geospatial foraging map, collectively support rapid and reliable decision-making. Through its MRRDC integration,

KabuTeach serves as a form of digital expert consultation service, analogous to free mycological evaluation services in Italy, adapted for rural Philippine communities. Usability evaluation with 102 respondents yielded a Grand Mean of 5.93 ("Agree"), with ease of learning emerging as the highest-rated dimension at 6.16 ("Strongly Agree"), confirming that the platform is intuitive and easy to adopt, even for users with limited digital literacy.

The primary limitation is the reliance on the UCI mushroom dataset, which represents North American species and may not fully reflect Philippine mushroom biodiversity. Future research will therefore focus on: (1) integrating Philippine-specific mushroom datasets collected and validated by MRRDC domain experts; (2) incorporating image processing and machine learning through mobile device cameras to enhance classification accuracy and reduce reliance on manual morphological inputs; and (3) expanding the usability evaluation to include broader stakeholder groups such as agricultural extension workers and public health officers. These directions will further enhance the real-world applicability of KabuTeach and contribute to safer, more sustainable mushroom foraging practices in rural communities.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Vilchor G. Perdido	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Melinda A. Beninsig	✓	✓		✓	✓		✓	✓		✓	✓	✓		
Daniel Marvin B. Ramel	✓	✓		✓	✓		✓	✓			✓	✓	✓	

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : **O**riting - **O**riginal Draft

E : **E**riting - **R**eview & **E**editing

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [VGP], upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Vilchor G. Perdido    is a faculty member in the Computer Science Department at Nueva Vizcaya State University, Bayombong, Nueva Vizcaya, Philippines. He received his BSc in Computer Science from Nueva Vizcaya State University – Bayombong Campus in 2003 and graduated Master's in Information Technology from the University of La Salette – Santiago City in 2011. He is currently pursuing his Doctor of Information Technology (DIT) at the University of the Cordilleras – Baguio City. He is a passionate programmer and researcher in the field of Information Technology. His research interests include information systems, web and mobile development, internet of things (IoT), and machine learning. His commitment to advancing IT research is complemented by his academic pursuits. He can be contacted at email: vgperdido@nvsu.edu.ph.



Melinda A. Beninsig    is a faculty member at the University of the Cordilleras, Baguio City, where she currently serves as the Program Chair of the Information Technology Department. She holds a master's degree in Mathematics and Information Technology. Her professional interests include advanced mathematics and Enterprise Resource Planning (ERP) systems. She also mentors and guides students as the adviser for BSIT and MIT capstone projects, supporting future IT professionals in their research and development work. She can be contacted at email: mabeninsig@uc-bcf.edu.ph.



Daniel Marvin B. Ramel    is a faculty member in the Department of Natural Sciences at the College of Arts and Sciences, Nueva Vizcaya State University (NVSU), Bayombong Campus. He holds a Bachelor of Science in Biology (1998) and a Master of Arts in Biology (2008) from Saint Mary's University, and a Master of Science in Biology (2018) from Central Luzon State University. He previously served as Director of the Mushroom Resources Research and Development Center (MRRDC) at NVSU, where he led initiatives in macrofungi diversity and domestication. He is now pursuing his Ph.D. in Food Innovation, Nutrition and Health at the Asian Institute of Technology in Thailand, further deepening His research interests in Macrofungi as functional foods. He is a member of the Mycological Society of the Philippines, Inc. (MSP) and the Philippine Consortium for Science, Mathematics and Technology, Inc. (PCSMT). He can be contacted at email: dmramel@nvsu.edu.ph.