

Integrating Artificial Intelligence into Environmental Education: A Rule-Based Expert System for Hornbill Conservation Awareness

Celine Hew Boon Ling, Eugene How, Soon Boon Ming, Soong Jien Yoong and *Nur Zareen Zulkarnain

Faculty of Artificial Intelligence and Cyber Security, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, Durian Tunggal, Melaka, Malaysia

*Corresponding Author

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ABSTRACT

Hornbills are unique birds inhabiting Southeast Asian tropical rainforests, such as in Malaysia, where they have an important role in maintaining forest biodiversity while acting as forest regulators and seed dispersers. Their numbers have, however, plummeted because of deforestation, habitat destruction, illegal poaching and hunting, among others. Field identification and field observation of species by experts is time-consuming and restricted because they cannot quantitatively estimate hornbill populations. The growing domain of artificial intelligence (AI) technologies offers new possibilities for more advanced wildlife tracking and conservation awareness through automation and smart data management. The article explains the design and implementation of a rule-based expert system with AI incorporation in environmental education on hornbill species and their conservation status. A rule-based system integrated with image classification is utilized to categorize ten widely spread species of hornbills in Malaysia and classify them under the respective International Union for Conservation of Nature (IUCN) Red List categories. A machine learning framework trained using hornbill images was incorporated into an easily accessible interface to ensure highest usability and accuracy. The evaluation confirmed that the system generated consistent recognition results with confidence levels above 90% for all species. Apart from its technical contribution, the system serves as an interactive learning platform that bridges artificial intelligence with biodiversity conservation. The system enables users to observe the ways AI models recognize species while being exposed to ecological and conservation information. This integration of technology and environmental education engenders critical thinking, interdisciplinarity, and Malaysian wildlife awareness by the public. The study confirms that AI-driven expert systems are effective means of conservation learning and awareness for maintaining national and international sustainability goals through technology-facilitated learning.

Keywords: Expert system; Artificial intelligence; Hornbill classification; Biodiversity; Conservation

INTRODUCTION

The use of artificial intelligence (AI) in education has widened the avenues of possibilities through which learners interact with complex scientific and environmental concepts. AI can be employed as a bridge between theoretical concepts and real-life application in environmental education so that students are able to perceive and learn about natural phenomena through data-driven means. With continuous loss of biodiversity globally, the role of technology in the spread of conservation awareness cannot be overstated. Artificial intelligence systems present efficient and interactive means of detecting, classifying, and analyzing ecological data with pertinent learning experiences combining environmental science and computational thinking.

Malaysian tropical rainforests are richly biodiverse with hornbills, which are now symbols of Malaysia's natural heritage. Hornbills are significant ecological seed dispersers with functions in forest regeneration and ecological balance. However, a few hornbill species have experienced significant population loss due to deforestation, habitat loss, poaching and illicit hunting. In the opinion of the International Union for Conservation of Nature (IUCN, 2024), many species such as the Helmeted and Rhinoceros Hornbills are presently "Threatened" while others such as the Oriental Pied Hornbill are "Least Concern" but with long-term threats in their environment.

Their loss would not just be causing disruption to forest communities but also diminish Malaysia's biodiversity inheritance.

Traditional research methodologies of hornbill study by manual observation and photo surveys have been widely practiced but are often limited by observer bias and logistical limitations. Field identification requires wide expertise and is difficult to scale in remote forest environments. Besides, visually similar species such as the Great and Wreathed Hornbills may prove difficult to identify without technical assistance. Such shortcomings proclaim the need for an intelligent system that can automate the process of classification and improve the accuracy of identification.

In this study, a rule-based expert system using AI techniques is proposed for identifying species of hornbills in a more effective way and for improving conservation education. There are three objectives of this study. The first is to automate hornbill identification using rule-based reasoning that detects main species characteristics such as casque shape, size, and coloration. The second objective is to improve the efficiency and accuracy of classification of hornbill species using machine learning for image-based classification over manual observation. The third objective is to spread data-aware conservation awareness via an easily accessible platform that allows students, educators, and conservationists to explore how AI assists in biodiversity conservation.

The system's design combines rule-based reasoning and machine learning classification in a single system. The rule-based component employs structured reasoning to match species features with known patterns, and the learned model reads visual information to predict outcomes based on learned image features. This integration approach allows students to understand symbolic thinking and pattern recognition as building blocks of AI. Positioning AI in an applied environmental context provides students with a concrete example of how technology supports problem-solving in authentic settings.

Through artificial intelligence and environmental learning integration, this study demonstrates the ability of intelligent systems to improve scientific learning based on interactivity and efficiency. The study not only supports technological development but also helps sustainability goals through ecological literacy and conservation participation. This study demonstrates that AI can serve both as a scientific tool and a learning medium, enabling users to understand and help preserve Malaysia's natural heritage. Furthermore, this initiative aligns with the United Nations Sustainable Development Goals (SDG), particularly SDG 13 (Climate Action) and SDG 15 (Life on Land), by promoting environmental education literacy and encouraging proactive participation in biodiversity conservation through technology-enhanced learning.

LITERATURE REVIEW

Environmental education has evolved significantly with the growing adoption of digital and intelligent technologies. As sustainability issues become more complex, educators and researchers have sought innovative approaches to make environmental education more interactive and accessible. Among the emerging technologies, AI has emerged as one of the most promising tools in this transformation, offering new ways to analyze data, visualize ecosystems, and encourage public participation in conservation efforts. At the same time, understanding the ecological challenges facing endangered species remains essential for meaningful environmental learning. This section reviews recent studies on the integration of AI in environmental education and examines the major environmental threats contributing to the decline of hornbill populations in Malaysia and the wider Asian region.

Artificial Intelligence in Environmental Education

The integration of AI tools has reshaped the delivery of environmental education by enabling students and the public to explore complex environmental concepts and theories through simulation, visualization, and intelligent feedback. Adaptive learning systems, chatbots, and virtual simulations help learners visualize environmental processes that are often inaccessible in real life (Arif et al., 2025). By processing large amounts of environmental data and providing adaptive responses, AI supports the shift from passive instruction to active, inquiry-based learning. It is now possible for students and learners to analyse environmental problems, predict outcomes, and

propose solutions through interactive platforms that transform abstract environmental and ecological information into engaging, data-driven experiences (Das et al., 2024; Lowan-Trudeau, 2023).

Existing Works

AI applications in environmental learning range from adaptive learning systems and virtual assistants to image-recognition tools that classify species or analyse ecological data. Machine learning models, particularly those used in classification and prediction, are increasingly incorporated into environmental science curricula to make learning more experiential. Konya and Nematzadeh (2024) reviewed recent AI applications in environmental science and engineering, showing that classification, pattern recognition, and predictive modelling are among the most effective tools for tasks such as biodiversity monitoring and pollution assessment. Their work shows that AI can transform how environmental data is processed and used for decision making. Similarly, Sachyani (2025) demonstrated that integrating AI into environmental education through creative tools such as digital comics and visualization activities improved students' engagement and comprehension of ecological interactions. An article by Rrustemaj (2025) describes how techniques such as virtual tutoring, automated assessment, and adaptive content delivery has been used effectively across domains. The same techniques can also be adapted for environmental education, supporting interactive and personalized learning.

Benefit and Challenges

Integrating artificial intelligence into environmental education enhances personalization, interactivity, and accessibility in learning. Adaptive systems tailor content to individual learners, while AI-driven simulations allow students to analyse authentic environmental data and visualize complex ecological interactions. Studies show that AI integration supports engagement and deep learning when aligned with clear instructional goals (Wang et al., 2024; Ifenthaler et al., 2024). In ecological contexts, classification and predictive models improve understanding of biodiversity and environmental monitoring (Konya et al., 2024). However, challenges persist regarding data quality, algorithmic transparency, and equitable access. Poorly curated datasets may bias model outcomes, while limited computational infrastructure can hinder implementation in resource-constrained settings. Ethical concerns about data privacy and the risk of overreliance on AI tools further emphasize the need for human oversight and pedagogical alignment (Rrustemaj, 2025; Zhai et al., 2024).

Environmental Threats to the Hornbill Population

Hornbills play an important ecological role as seed dispersers that help maintain forest balance. However, their populations in Asia, including Malaysia, are declining due to increasing human activities. These birds depend on mature forests for nesting and feeding, making them highly vulnerable to environmental disturbances. The main factors threatening their survival include deforestation, habitat loss, poaching, and illegal hunting (BirdLife International, 2022).

Deforestation and Habitat Loss

The hornbill populations have declined rapidly as their natural habitats continue to be threatened by deforestation and extensive logging causing destruction to their habitats. The loss of large hollow trees, which serves as essential nesting sites, further exacerbates this decline (Misni et al., 2017). As hornbills are large-sized cavity nesters, the availability of trees with substantial girths and large cavities are crucial for providing suitable nesting sites to sustain their populations (Kaur, 2020; Misni et al., 2017). In Peninsular Malaysia, over 3.7 million hectares of forest loss were reported (Aik & Perumal, 2017), affecting many bio-diversities and wildlife (Abdullah & Hezri, 2008). Planned developments are also one of the environmental threats endangering the hornbill population (Alamgir et al., 2020) particularly in Sarawak, Malaysia where extensive areas of its intact forests have been lost in recent decades (Jaafar et al., 2020; Gaveau et al., 2014) thus calling for urgent conservation efforts by the Sarawakian government.

Poaching and Illegal Hunting

The severity of poaching poses significant threats to the hornbill population particularly the Helmeted Hornbill also known by its scientific name as *Rhinoplax vigil*, which is currently under the threat of trade for its bright-colored casque (Beastall et al., 2016; Collar, 2015;) that is a material often sought after for carving ornamental items (Beastall et al., 2016). In 2015, the Helmeted Hornbill was uplisted from ‘Near Threatened’ to ‘Critically Endangered’ on the International Union for Conservation of Nature (IUCN) Red List of Threatened Species due to these excessive poaching activities (Aik & Perumal, 2017).

METHODOLOGY

This study adopts a design and development methodology to develop an AI-based expert system to support environmental education and wildlife conservation awareness. This study focuses on ten species of Malaysian hornbills, applying rule-based reasoning as well as classification principles to support the automation of species identification and ease in learning for end-users. The methodology includes four major components which are system design, rule-based reasoning and classification, system architecture, and implementation.

System Design

The system was conceptualized to be a learning and conservation support tool for users, from students to educators and conservationists, to identify hornbill species and their ecological relevance. The design began with target species determination and selection of visual and ecological features that could be employed to distinguish between them. They included body size, casque shape, coloration, and habitat. Information was obtained from publicly accessible biodiversity databases and field surveys reported in the literature.

A knowledge base was then built with factual data on ten common hornbill species found in Malaysia: Helmeted, Rhinoceros, Wrinkled, Oriental Pied, Black, Plain-pouched, White-crowned, Bushy-crested, Great, and Wreathed Hornbills. For each species, corresponding characteristics and conservation status categories were defined in terms of the International Union for Conservation of Nature (IUCN, 2024). These facts formed the foundation of the reasoning mechanism of the expert system.

Target User

The expert system is mainly educational, whereby pupils, educators, and the public can access information on hornbill species via an interactive interface. Users can identify different hornbill species and determine whether each has been listed as “Threatened”, “Near Threatened”, or “Least Concern” through image uploading. The same system can also aid forest rangers, conservation organizations, and researchers by allowing quick and correct hornbill species identification in the field. By fulfilling this dual function, the system helps to promote both environmental education and effective conservation awareness.

Rule-Based Reasoning and Classification

The expert system uses a classification-centered approach in an AI environment using rule-based reasoning for hornbill species identification against known visual and ecological attributes. A system of “if-then” rules was created that relied on such species characteristics as body weight, casque shape, coloration scheme, and environment. For instance, if the bird is very large with a heavy red casque and occurs in primary forests at low elevations, then the system diagnoses it as a Helmeted Hornbill, a threatened species. Each hornbill species is embodied in a unique set of features that collectively form the knowledge base of the system.

The inference engine operates in a forward-chaining methodology beginning from provided attributes and repeatedly moving through the rule base until it reaches the point where it determines a condition has been fulfilled. When a rule is fired, the system produces an output indicating the determined species and its conservation category, i.e., “Threatened”, “Near Threatened”, or “Least Concern”. This rule-based reasoning technique is equivalent to classification system logic commonly utilized in machine learning, where there is an

association of defined features with specific output classes. Table 1 below presents 13 rules used in the expert system to perform forward-chaining inferencing.

Table 1. Rule set used in the expert system.

Rule 1	IF the hornbill is very large in size AND has a heavy red casque AND prefers lowland primary forests, THEN the species is Helmeted Hornbill.
Rule 2	IF the hornbill is large in size AND has a yellow casque curving upward AND is found in lowland to hill rainforests, THEN the species is Rhinoceros Hornbill.
Rule 3	IF the hornbill is medium in size AND has a wrinkled-looking casque AND lives in lowland forests of Borneo, THEN the species is Wrinkled Hornbill.
Rule 4	IF the hornbill is medium in size AND has a black and white body with a small casque in yellow or white AND is active in open and secondary forests, THEN the species is Oriental Pied Hornbill.
Rule 5	IF the hornbill is medium to large AND has a black beak with a simple casque AND prefers lowland dipterocarp forests, THEN the species is Black Hornbill.
Rule 6	IF the hornbill is large in size AND has a long, narrow casque and no distinctive dark bar on its throat pouch AND is found in hill and lowland forests of northern Peninsular Malaysia or Thailand, THEN the species is Plain-pouched Hornbill.
Rule 7	IF the hornbill is large in size AND has a distinct white crown and shaggy crest AND lives in lowland to hill forests or plantations, THEN the species is White-crowned Hornbill.
Rule 8	IF the hornbill is small to medium AND has a bushy crest AND lives in lowland or secondary rainforest, THEN the species is Bushy-crested Hornbill.
Rule 9	IF the hornbill is very large in size AND has a bright yellow casque with black markings AND prefers mature forest tracts, THEN the species is Great Hornbill.
Rule 10	IF the hornbill is large in size AND has a curved casque, black body, white tail and has a distinctive dark bar on its throat pouch AND lives in evergreen forests up to mountain regions, THEN the species is Wreathed Hornbill.
Rule 11	If the hornbill species is Helmeted Hornbill OR Rhinoceros Hornbill OR Wrinkled Hornbill OR Plain-pouched Hornbill OR Great Hornbill OR Wreathed Hornbill THEN category is Threatened.
Rule 12	If the hornbill species is Oriental Pied Hornbill THEN category is Least Concern.
Rule 13	If the hornbill species is Black Hornbill OR White-crowned Hornbill OR Bushy-crested Hornbill THEN category is Near Threatened.

The system integrates both rule-based reasoning and machine learning to enhance hornbill species identification and understanding. The rule-based component extracts key features and characteristics such as body size, casque color and size, and habitat from hornbill images. It then guides users in interpreting these traits to classify the species accurately. To complement this, Google's Teachable Machine was used to train an image classification model on a curated dataset of hornbill images. The model learns to recognize visual patterns and distinguishing features of various hornbill species with different behaviors and positions. Once trained, it is deployed within the system to perform automated species classification.

While the machine learning component predicts or classifies the hornbill species, the rule-based system explains and verifies the classification based on predefined expert knowledge. This combination balances analytical accuracy with educational value, allowing users to see how expert systems and machine learning work together to deepen understanding of biodiversity through artificial intelligence.

System Architecture

Hornbill expert system architecture was designed hybrid which combines rule-based reasoning and image-based classification. With such architecture, the system both acts as a conservation support system and as a learning tool. Five important components of its architecture are (i) user interface, (ii) knowledge base, (iii) inference engine, (iv) integration of the trained model, and (v) output module.

The user interface serves as the point of interaction between users and the system. It is a simple interactive stage where users can input hornbill images that will be used by the system to identify features like body size, casque shape, color, and type of habitat. The interface was designed with Python in mind to make it accessible to both learners and teachers. Its easy-to-use interface allows students and conservationists to use the system without any trouble in leveraging AI concepts through learning biodiversity.

The knowledge base retains information in structured form and rule sets for ten hornbill species in Malaysia that are Black Hornbill, Bushy-crested Hornbill, Great Hornbill, Helmeted Hornbill, Wreathed Hornbill, White-crowned Hornbill, Rhinoceros Hornbill, Plain-pouched Hornbill, Oriental Pied Hornbill, and Wrinkled Hornbill. Each rule sets out the combination of hornbill features and the corresponding species name. For instance, a large body size with an upcurved yellow casque and a habitat in rainforest lowlands corresponds to the Rhinoceros Hornbill. All the conservation categories were projected using the International Union for Conservation of Nature (IUCN, 2024) data but condensed into three kinds that are “Threatened”, “Near Threatened”, or “Least Concern”. Knowledge base provides the facts based on the inference engine and ensures the accuracy of the educational material in the system.

The inference engine uses the user input through forward-chaining reasoning. The engine compares the provided attributes against the knowledge base rules until a matching condition is met. When a rule is triggered, the engine produces an output consisting of the species' name and its conservation status. This logical operation demonstrates to students how expert systems mimic human decision-making through structured reasoning.

Apart from the rule-based reasoning system, the system features a classification model that has been trained using Google Teachable Machine. The system utilized a small image dataset of various species of hornbills to train the model to learn significant visual patterns. The trained model was then exported and imported into the Python environment to assist the inference engine in classification tasks. Once the image is uploaded by the user, the model estimates the probable species, and this is checked against the rule-based result to make it more accurate. This integration allows the user to observe how the machine learning complements expert systems, thereby maintaining the application functional as well as educational.

The output module displays the final classification result. It displays the hornbill species name, prediction confidence level and its conservation category. The interface provides real-time visual and textual feedback to enable learners to associate observed traits with environmental awareness. The module unites the system's double aim of promoting environmental awareness and demonstrating the applied nature of AI in environmental education.

System Implementation

Expert system implementation was focused on translating conceptual design into an operational framework combining rule-based thinking and image-based classification. The software development was made to achieve technical correctness and pedagogic feasibility in order that the system may be employed as an effective species identification tool and as an educational utility for understanding artificial intelligence applications for environmental preservation.

The system was coded using the Python programming language within the Anaconda environment, where package management and bundling of multiple components at once were supported. The development and testing were accomplished through Visual Studio Code. Python was used because of its versatility and simplicity, making it easy for students and instructors to easily explore how artificial intelligence principles are applied in real-world applications. The whole process of development had a design-test-refine loop to guarantee stability and clarity of user interaction.

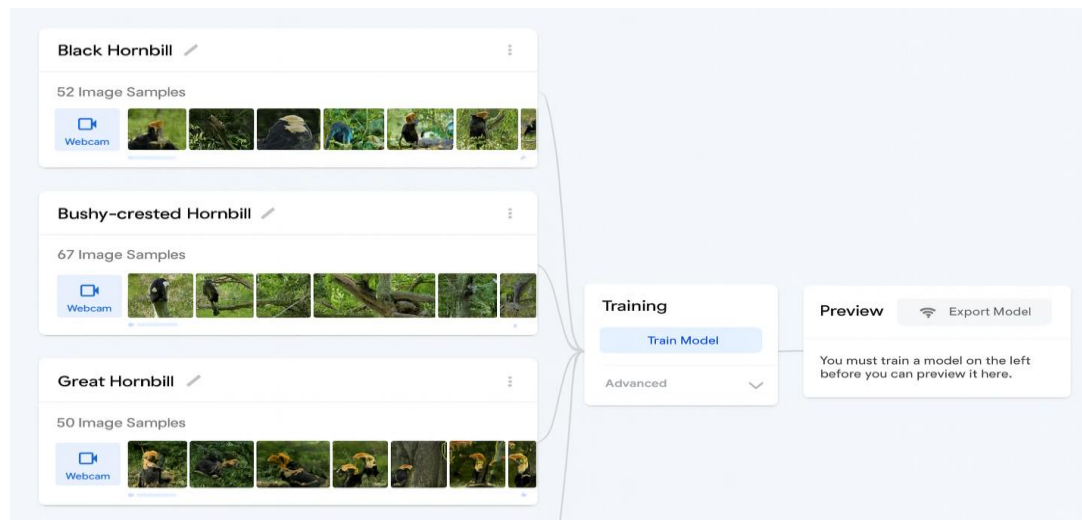


Figure 1. Model training using Google Teachable Machine.

Google Teachable Machine was used to train a simple image classification model from a carefully curated dataset consisting of ten hornbill species. The Teachable Machine framework internally applies a convolutional neural network (CNN) for image training and recognition, allowing simple deployment without complex coding. The images were each tagged with the species' names, and the model was trained to recognize distinctive visual patterns for each of the species. For each species category of the hornbills, at least 50 images of the species were used to train the model. The images for training were sourced from publicly available Google Images results and were carefully placed in different folders based on their species. The number of images used in training each species category was made close to one another to guarantee that the trained model is neutral. The trained model was then exported in TensorFlow format and placed within the Python environment to allow automated identification of species. It supports the rule-based reasoning component by increasing the reliability of classification.

The model was tested and validated on image-based inputs. A 70-30 ratio was used in training and testing the model. Various images of hornbills with different species were uploaded and processed using the trained model. Results were compared to authentic species information from the International Union for Conservation of Nature (IUCN, 2024) to confirm the reliability of both reasoning processes. The results showed that the system was able to classify hornbill species with consistent confidence levels and provide the appropriate conservation categories, aligning with IUCN data. The interface is kept minimal such that users can upload a picture and instantly get the identified species and its conservation status. The lightweight design enables the system to run on standard computers without any additional installation procedures, making it ready to be used for demonstrations in classrooms, lab exercises, or public awareness programs.

The deployment realized an operational AI-driven expert system capable of recognizing hornbill species and providing effective learning experiences. The integration of rule-based reasoning and image-based classification not only enhanced the accuracy of identification but also demonstrated the potential of technology in facilitating environmental education. Students can explore artificial intelligence ideas and biodiversity issues at the same time on a single interactive site using this system. Beyond its technical capabilities, the deployment also highlights the broader role of AI in supporting sustainable development. By enabling users to understand species diversity, conservation status, and the consequences of habitat loss, the system cultivates environmental responsibility and critical thinking among learners. It empowers educators to incorporate real-world data and AI

applications into their lessons, thereby bridging computational literacy with ecological awareness. As a result, this system directly supports SDG 13 (Climate Action) and SDG 15 (Life on Land).

RESULTS AND DISCUSSION

The hornbill image classification system was designed to automatically recognize ten hornbill species that are found in Malaysia which are the Black Hornbill, Bushy-crested Hornbill, Great Hornbill, Helmeted Hornbill, Wreathed Hornbill, White-crowned Hornbill, Rhinoceros Hornbill, Plain-pouched Hornbill, Oriental Pied Hornbill, and Wrinkled Hornbill. The back-end classification model utilized a machine learning model that was trained using a standard classification approach and then implemented in a graphical user interface (GUI) for verification and user convenience. The GUI was intended to facilitate users in uploading an image, visualizing the results of the predictions, and seeing the conservation status of the species that were detected. Apart from being a testing site, the interface also acts as an educator that shows how artificial intelligence can be used in wildlife identification and learning diversity.

System Performance

The system was tested with hornbill images of varying orientations, lightings, and backgrounds to test the stability of model recognition. Figure 2 shows a sample result for a sample image of Black Hornbill. The model correctly predicted the species with 99.29% confidence level and displayed its respective conservation status as “Near Threatened” which is correct according to the International Union for Conservation of Nature (IUCN, 2024). The GUI visualization includes a horizontal confidence bar that represents the probability distribution of all possible species. This enables users to visualize the confidence of the model and, therefore, make the classification more transparent. The unequivocal dominance of the top prediction, reflected in the confidence plot, indicates that the machine learning model constructed an explicit decision boundary in the feature space that well is discriminated against the correct class from the remaining nine species.

The same test procedure was extended to the other hornbill species to validate the consistency of the model across different samples. Figure 3 shows additional examples of the classification interface, which consistently provide correct identifications of species along with correct conservation labels. The interface is of high confidence even when images vary in light and background, displaying the strength of the model. GUI design is maintained as simple and informative, with every prediction displayed along with its percentage confidence level, image, and conservation category. This simple explanation does not only optimize usability but also connects the technical outcome to its ecological basis, allowing users to understand both how AI classification works and why hornbill conservation matters.

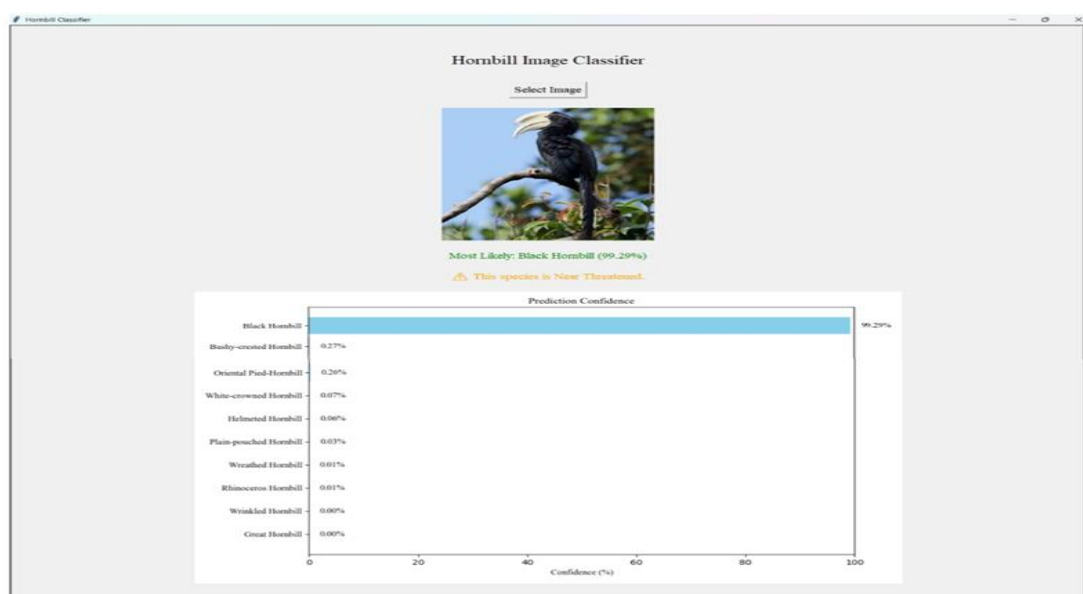


Figure 2. Detailed confidence level for specific class prediction.

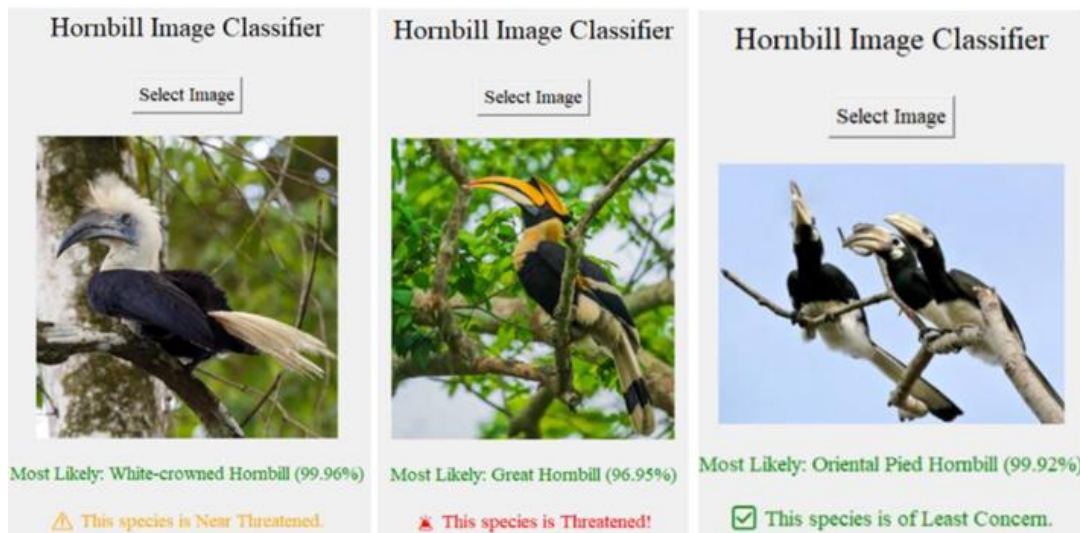


Figure 3. Examples of the classification interface that includes three threats level.

Table 2 summarizes the classification results of model testing for all ten species. The classifier maintained the maximum levels of prediction confidence, mostly over 90%, on approximately 20 to 30 unseen test images. The Helmeted Hornbills and the Rhinoceros were identified perfectly with highly confident levels due to their regular casque shape and large body size. The Oriental Pied and White-crowned Hornbills were also identified accurately based on their pale coloration and facial coloration. Minor confusion occurred between the Great and Wreathed Hornbills, whose superimposing colors and resembling casque shapes often lead to visual ambiguity even to field observers. Such misclassifications are unavoidable in fine-grained image classification problems where inter-species difference is fine.

Table 2. Classification outcomes of model testing on ten different hornbill species.

No.	Hornbill Species	Conservation Status	Observed Prediction Confidence Level (%)*	Classification Outcome
1.	Black	Near Threatened	99.29	Near Threatened
2.	Bushy-crested	Near Threatened	99.53	Near Threatened
3.	Great	Threatened	96.95	Threatened
4.	Helmeted	Threatened	98.14	Threatened
5.	Wreathed	Threatened	96.31	Threatened
6.	White-crowned	Near Threatened	98.9	Near Threatened
7.	Rhinoceros	Threatened	99.34	Threatened
8.	Plain-pouched	Threatened	99.01	Threatened
9.	Oriental Pied	Least Concern	99.92	Least Concern
10.	Wrinkled	Threatened	97.76	Threatened

* Confidence level values were derived from the model's graphical output at test run and represent average observed levels across sample runs.

The findings in Table 1 and Figures 2 and 3 consistently indicate that the expert system is very accurate and robust in identifying species. The classifier consistently produced confidence levels higher than 90%, consistent with the validation accuracy attained at training. These findings validate that the machine learning algorithm generalized to new data effectively, irrespective of variations in lighting or background. The qualitative findings also validate that morphological characteristics such as casque shape, beak curvature, and plumage pattern are robust distinguishing features for hornbill identification. The minor ambiguity between visually confused species is anticipated and strengthens documented field-identification difficulties and underscores the capability of AI to support human professionals in reducing such mistakes.

Although this analysis was based on manual trials instead of statistical benchmarking, the outcomes provide strong evidence of the model's reliability under realistic conditions. Interactive visualization of confidence scores by the GUI improves interpretability and encourages trust in the predictions of the system. By allowing users to experience prediction confidence directly, the system introduces an implicit learning dimension regarding how artificial intelligence manages uncertainty and confidence estimation.

Education and Conservation Impact

Aside from technical accuracy, the educational and social impacts of the expert system are large. The GUI turns what would otherwise be a computation-only system into an experiential learning platform. Not only can users test hornbill images to determine their species but also regarding the conservation status of their species. This approach fosters environmental education objectives by placing scientific facts into a fun and interactive context. The integration of IUCN Red List categories such as "Threatened", "Near Threatened", or "Least Concern" bridges AI with environmental literacy, enabling users to connect technology with real-world sustainability issues.

For students, the system teaches how AI can be employed to solve environmental issues and how digital skills can be learned. The system offers cross-disciplinary learning opportunities where computer science and environmental science intersect with sustainability. Students get to learn key concepts in AI such as feature extraction and classification from real-world conservation data. For conservation professionals, the model's strong recognition capability provides a lightweight tool that can contribute towards preliminary species identification when conducting field surveys, particularly in regions with limited expert presence. Government agencies and wildlife organizations can also adapt this design to fit public-awareness programs or citizen-science programs focused on hornbill monitoring.

CONCLUSION

The hornbill expert system effectively proves AI applications' capability to enrich environmental education and wildlife awareness. By combining rule-based reasoning with image-based classification, the system provides an engaging and interactive learning experience for hornbill species identification while communicating their conservation status. Integration of a machine learning classifier into an intuitive interface enables students to experience how computer vision processes images and make decisions, bridging the gap between technological and environmental knowledge. The test outcomes revealed that the system works with very high accuracy and stability for all ten species of hornbills with prediction confidence above 90%. These findings validate the system's value not only as a reliable tool for classification, but also as an educational tool that breaks down complex AI concepts into simple learning experiences.

This study points to the ways in which AI-driven methods can transform traditional environmental education by extending experiential learning and enhancing digital literacy. Through interactive classification and conservation-based comments, students are encouraged to explore the intersection of technology and sustainability. The system also demonstrates validity in real-world application for forest rangers, scientists, and conservation groups seeking practical methods of hornbill identification. Its pedagogical nature ensures that students and the public can meaningfully engage with information pertaining to conservation efforts, encouraging environmental stewardship through learning technology. By supporting education on biodiversity and sustainable ecosystems, the system directly contributes to the realization of SDG 15 (Life on Land), while

its integration into environmental education frameworks supports SDG 13 (Climate Action) through increased awareness and responsible stewardship of natural resources.

Future work can generalize the quantitative analysis of the model with more extensive datasets and performance measurements in computing such as precision, recall, and F1-score. Further refinement of user interface and inclusion of visualization explainable-AI functionalities would enhance interpretability and transparency for learners. The system could also be adapted for web or mobile deployment to support outdoor biodiversity learning and citizen-science activities. In summary, this work provides a foundation for artificial intelligence integration into environmental learning and demonstrates how technology might be efficiently utilized to enhance conservation awareness and sustainability literacy in Malaysia and beyond.

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