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Expert System for Diagnosing Black Glutinous Rice Plant Diseases Using Forward Chaining and Backward Chaining Methods

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A B S T R A C T

Black glutinous rice (*Oryza sativa L. var. glutinosa*) is an important local crop in Indonesia whose productivity is frequently affected by pests and diseases. Accurate diagnosis remains challenging because disease symptoms are often similar and farmers have limited access to agricultural experts. This study proposes a web-based expert system that integrates Forward Chaining and Backward Chaining within a sequential hybrid inference workflow for diagnosing diseases in black glutinous rice plants. The system was developed using the Expert System Development Life Cycle (ESDLC), while expert knowledge was acquired through interviews with the Puspamukti Farmers Group, agricultural experts from Universitas Perjuangan Tasikmalaya, field observations, and literature review. The resulting knowledge base consists of 30 symptoms, 6 pests and diseases, and IF–THEN production rules. In the proposed inference mechanism, Forward Chaining generates candidate diseases from user-selected symptoms, whereas Backward Chaining verifies the inferred candidate before confirming the final diagnosis and presenting treatment recommendations. The system was evaluated using Black Box Testing, expert validation involving 20 representative test cases, and comparative inference analysis. All system functions operated correctly, and expert validation showed a diagnostic accuracy of 95%, with 19 of 20 diagnoses matching expert assessments. The proposed sequential hybrid inference workflow provides a more systematic and

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consistent reasoning process than conventional Forward Chaining by incorporating an additional verification stage before confirming the final diagnosis. These findings demonstrate that the proposed expert system can effectively support early diagnosis and disease management for black glutinous rice plants.

1. INTRODUCTION

Black glutinous rice (*Oryza sativa L. var. glutinosa*) is one of Indonesia's indigenous rice varieties with high economic and functional value due to its rich anthocyanin content (Kristamtini et al., 2018), a natural antioxidant compound that provides various health benefits. Compared with many other rice varieties, black glutinous rice contains higher levels of anthocyanins, making it widely recognized as a functional food and a promising agricultural commodity in Indonesia. In Tasikmalaya Regency, West Java, black glutinous rice is cultivated by local farmers and contributes significantly to the regional agricultural economy. However, its productivity is frequently threatened by various pests and diseases (IRRI, 2013), including the brown planthopper (*Nilaparvata lugens*), yellow stem borer (*Scirpophaga incertulas*), rice blast (*Pyricularia oryzae*), bacterial leaf blight (*Xanthomonas oryzae pv. oryzae*), and sheath rot (*Rhizoctonia solani*). If these diseases are not identified at an early stage, they may significantly reduce crop productivity and even lead to crop failure.

In current farming practices, disease identification largely depends on farmers' visual observations and personal cultivation experience. However, several rice diseases exhibit similar symptoms, making accurate diagnosis difficult. In addition, the limited availability of agricultural experts and extension officers restricts farmers' access to timely consultation when disease outbreaks occur. These challenges highlight the need for an intelligent system capable of capturing expert knowledge to support faster, more consistent, and easily accessible disease diagnosis for farmers (FAO, 2022).

Expert systems represent one of the applications of artificial intelligence that utilize a knowledge base and an inference engine to emulate the reasoning process of human experts (Russell & Norvig, 2021). In rule-based expert systems, Forward Chaining performs inference by reasoning from known facts (symptoms) to a disease diagnosis, whereas Backward Chaining starts from a disease hypothesis and verifies it against the observed symptoms (Jackson, 1999). Previous research by Honggowibowo demonstrated that integrating these two inference methods in a web-based expert system could effectively support the diagnosis of rice diseases through a systematic reasoning process that is accessible to farmers (Honggowibowo, 2009).

Previous studies have mainly focused on applying either Forward Chaining or Backward Chaining as independent inference mechanisms (Lestari & Nugroho, 2021; Mochammad & Wibowo, 2020). Few studies explicitly describe how both methods can be integrated into a sequential reasoning workflow, in which Forward Chaining generates candidate diseases while Backward Chaining validates the inferred hypothesis before producing the final diagnosis. Consequently, the contribution of hybrid inference to improving reasoning consistency remains insufficiently discussed.

Although numerous studies have applied Forward Chaining, Backward Chaining, and other inference methods for diagnosing rice diseases, most have focused on rice crops in general rather than specifically on black glutinous rice. Moreover, previous studies commonly employed a single inference mechanism or emphasized disease identification without incorporating rule verification. Consequently, research on integrating Forward Chaining and Backward Chaining for diagnosing diseases in black glutinous rice remains limited. Therefore, this study proposes a web-based expert system that integrates both inference methods. In the proposed system, Forward Chaining is used to generate candidate diseases based on user-selected symptoms, while Backward Chaining verifies the inferred diagnosis before presenting the final diagnosis and treatment recommendations. This hybrid inference mechanism is expected to improve diagnostic consistency and assist farmers in making more appropriate disease management decisions.

2. METHODS

This study adopted the Expert System Development Life Cycle (ESDLC) proposed by Durkin (1994) as the development methodology for designing and implementing the proposed expert system.

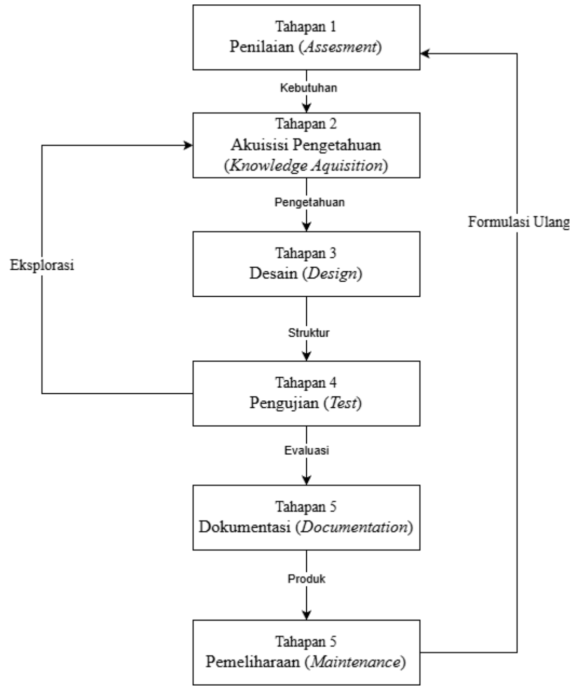

Figure 1. Expert System Development Life Cycle (ESDLC) Model

2.1. Knowledge Acquisition

Knowledge acquisition is the process of collecting and validating expert knowledge to construct the knowledge base of the expert system. In this study, knowledge was obtained through interviews with the Puspamukti Farmers Group in Cigalontang District and experts from the Agrotechnology Study Program at Universitas Perjuangan Tasikmalaya, supported by field observations and a comprehensive literature review. The acquired knowledge resulted in a knowledge base consisting of 30 symptoms and 6 pests and diseases, which were subsequently represented as IF–THEN production rules to support the hybrid inference process using the Forward Chaining and Backward Chaining methods.

Knowledge acquisition is one of the most important stages in expert system development because the quality of the knowledge base directly determines inference accuracy (Durkin, 1994; Giarratano & Riley, 2005).

Table 1. List of Pests and Diseases Affecting Black Glutinous Rice Plants

Code	Pest or Disease
P01	Bacterial Leaf Blight (Scirpophaga incertulas)
P02	Brown Planthopper (Nilaparvata lugens)
P03	Rice Blast Disease (Pyricularia oryzae)
P04	Yellow Stem Borer (Xanthomonas oryzae pv. oryzae)
P05	Root and Sheath Rot (Rhizoctonia solani)
P06	Bird Pests / Munias (Lonchura spp.)

Table 2. Disease and Pest Symptoms

Code	Symptom Description
G01	Daun berubah warna menjadi kuning pucat
G02	Ujung daun mengering seperti terbakar
G03	Daun terdapat bercak coklat keabu-abuan
G04	Daun terdapat bercak bundar dengan tepi kehitaman
G05	Daun melipat atau menggulung ke atas
G06	Batang berlubang dan mudah patah
G07	Terdapat serbuk seperti serbuk gergaji pada batang
G08	Malai tidak keluar sempurna (malai terbungkus pelepah)
G09	Malai keluar tetapi gabah tidak berisi (hampa)
G10	Daun terdapat lendir atau lapisan berminyak
G11	Batang busuk dan berbau tidak sedap
G12	Daun mengering dari ujung ke bawah
G13	Pertumbuhan tanaman terhambat
G14	Warna daun belang antara hijau tua dan muda
G15	Terdapat serangga kecil berwarna coklat di pangkal batang
G16	Daun terdapat titik-titik putih kecil
G17	Tanaman rebah sebelum panen
G18	Akar mudah tercabut dan busuk hitam
G19	Daun bawah mengering lebih cepat dari daun atas
G20	Gabah mudah rontok saat digoyang
G21	Permukaan daun tampak keperakan
G22	Daun muda menggulung dan kering
G23	Terdapat burung memakan malai saat hampir panen
G24	Terdapat bercak ungu atau coklat pada batang
G25	Jumlah anakan berkurang drastis
G26	Padi gagal berbunga meskipun usia tanam cukup
G27	Daun menggulung di pagi hari dan membuka di sore hari
G28	Daun terdapat benang halus atau jaring
G29	Daun tampak berlubang-lubang kecil
G30	Warna gabah kehitaman atau berjamur setelah panen

2.2 Rule Base and Hybrid Inference

The rule base represents expert knowledge derived from the decision tree model, which describes the reasoning process through hierarchical relationships between symptoms and diseases. This knowledge is encoded as IF–THEN production rules that serve as the foundation of the inference mechanism in the expert system (Jackson, 1999; Russell & Norvig, 2021).

During the diagnosis process, the rules are utilized by the Forward Chaining method to infer candidate diseases from user-reported symptoms, while the Backward Chaining method verifies the inferred diagnosis by tracing the supporting symptoms. Consequently, the rule base provides a structured representation of expert knowledge and supports a systematic and consistent hybrid inference process.

Figure 2. Architecture of the Proposed Expert System

1. Forward Production Rule
   The production rules used by the Forward Chaining mechanism represent the relationship between symptoms and diseases. The inference process starts from user-selected symptoms and generates a candidate disease when all required conditions are satisfied. An example of the production rule is shown below.

$$R_1 : \{G1, G3, G4, G28\} \rightarrow P01$$

   Rule R1 indicates that when symptoms G1, G3, G4, and G28 are simultaneously observed, the inference engine generates P01 (Bacterial Leaf Blight) as the candidate disease.
2. Verification Rule
   Once a candidate disease has been generated, the Backward Chaining mechanism verifies whether the candidate satisfies all supporting symptoms before confirming the diagnosis.

$$Goal = P01$$

$$Verify(G1, G3, G4, G28)$$

Unlike the production rule used in Forward Chaining, the verification stage does not introduce a new IF–THEN rule. Instead, the system evaluates whether the candidate disease generated by Forward Chaining satisfies all supporting symptoms defined in the knowledge base.

3. Hybrid Inference Process

   The proposed expert system employs a hybrid inference mechanism that integrates Forward Chaining and Backward Chaining into a sequential reasoning workflow. Initially, the symptoms selected by the user are stored as working memory and processed using Forward Chaining to generate a candidate disease. Rather than directly presenting the inferred result, the candidate is subsequently verified through Backward Chaining by evaluating whether all supporting symptoms satisfy the corresponding production rule. The diagnosis is confirmed only after the verification process is successfully completed, after which the system presents the final diagnosis together with the corresponding treatment recommendations. This sequential workflow ensures that diagnosis generation and diagnosis verification are performed as two complementary reasoning stages within a single inference mechanism (Honggowibowo, 2009). The overall hybrid inference workflow is illustrated in **Figure 3**.

Figure 3. Hybrid Inference Process

Unlike conventional rule-based expert systems that directly present the diagnosis after Forward Chaining, the proposed approach incorporates an additional verification stage using Backward Chaining. This hybrid inference workflow improves the consistency of the reasoning process by ensuring that the inferred candidate disease satisfies the supporting knowledge before the final diagnosis is confirmed.

2.3. System Evaluation

The proposed expert system was evaluated to assess both its functional performance and the reliability of the hybrid inference mechanism. The evaluation consisted of three stages: (1) Black Box Testing to verify system functionality, (2) Expert Validation to compare the system-generated diagnoses with expert assessments, and (3) Comparative Inference Analysis to demonstrate the contribution of the hybrid inference mechanism. Black Box Testing is commonly applied to verify software functionality without considering internal program structures (Pressman & Maxim, 2020).

1. Blac Box testing
   Black Box Testing was conducted to evaluate the functionality of the proposed expert system based on input and output behavior without considering the internal program structure. The evaluation covered all major system functions, including user authentication, symptom and disease data management, rule base management, the diagnosis process, and the presentation of diagnostic results. A function was considered valid when the actual output matched the expected output.

Table 3. Results of Black Box Testing

No	System Function	Expected Result	Status
1	Login	User authenticated successfully	Valid
2	Symptom Management	CRUD completed	Valid
3	Disease Management	CRUD completed	Valid
4	Rule Base Management	Rules stored correctly	Valid
5	Diagnosis Process	Diagnosis generated	Valid
6	Diagnosis Result	Treatment recommendation displayed	Valid

All system functions operated correctly without functional errors, indicating that the proposed expert system satisfies the predefined functional requirements.

2. Expert Validation
   Expert validation was performed by comparing the diagnoses generated by the expert system with those provided by domain experts using a set of predefined test cases. Each test case consisted of the same combination of symptoms, allowing a direct comparison between the system-generated diagnosis and the expert's diagnosis. The diagnostic accuracy of the proposed system was calculated using Equation (3).

Table 4. Representative Expert Validation

Case	Expert	System	Agreement
1	P01	P01	✓
2	P02	P02	✓
3	P02	P01	✗

The diagnostic accuracy of the proposed expert system was calculated based on the agreement between the system-generated diagnoses and the expert diagnoses using Equation.

Based on the expert validation results, 19 out of 20 test cases produced the same diagnosis as the domain experts. Therefore, the diagnostic accuracy of the proposed system is calculated as follows.

$$\text{Accuracy} = \frac{19}{20} \times 100 = 95\%$$

The proposed expert system achieved a diagnostic accuracy of 95%, indicating a high level of agreement between the diagnoses generated by the hybrid inference mechanism and those provided by domain experts.

The remaining test case produced a different diagnosis due to the similarity of symptoms shared by multiple diseases. In this case, the Forward Chaining mechanism generated a relevant candidate disease, while the Backward Chaining verification stage evaluated the supporting production rules before confirming the final diagnosis. This finding indicates that the proposed hybrid inference mechanism provides a consistent reasoning process, although its performance remains dependent on the completeness of the knowledge base and production rules.

3. Comparative Inference Analysis

   The comparison focuses on the reasoning workflow rather than diagnostic accuracy because both approaches use the same knowledge base and production rules.

Table 5. Comparative Inference

Inference Stage	Forward Chaining	Hybrid FC-BC
Candidate Disease	✓	✓
Rule Verification	-	✓
Final Diagnosis	Direct	Verified
Reasoning Consistency	Medium	High

The current evaluation was limited to 20 representative cases validated by domain experts. Future studies should involve larger datasets and additional evaluation metrics.

3. RESULTS AND DISCUSSION

3.1. System Implementation

Figure 4 presents the diagnosis interface of the proposed expert system. Users are required to answer a series of symptom-related questions by selecting Yes or No according to the observed condition of the black glutinous rice plant. For example, symptom G19 describes the condition in which the lower leaves dry more rapidly than the upper leaves. The confirmed symptoms are stored as the initial facts (working memory) and processed by the hybrid inference engine to identify the candidate disease according to the IF–THEN production rules stored in the knowledge base.

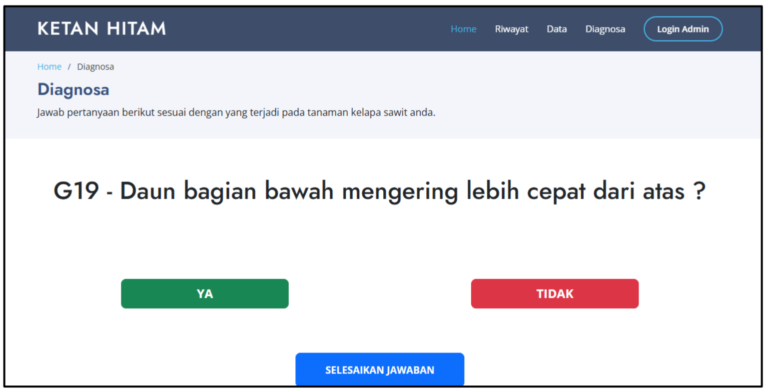

Figure 4. User Diagnosis Interface

Figure 5 shows the diagnosis result generated by the proposed expert system after the consultation process. The interface presents the user's identity and the selected symptoms, indicating whether each symptom is present (Yes) or absent (No). The confirmed symptoms are stored as the initial facts (working memory) and processed by the Forward Chaining inference engine to identify the candidate disease. The inferred candidate is subsequently verified using Backward Chaining, ensuring that the diagnosis is consistent with the corresponding production rules before the final diagnosis is displayed to the user.

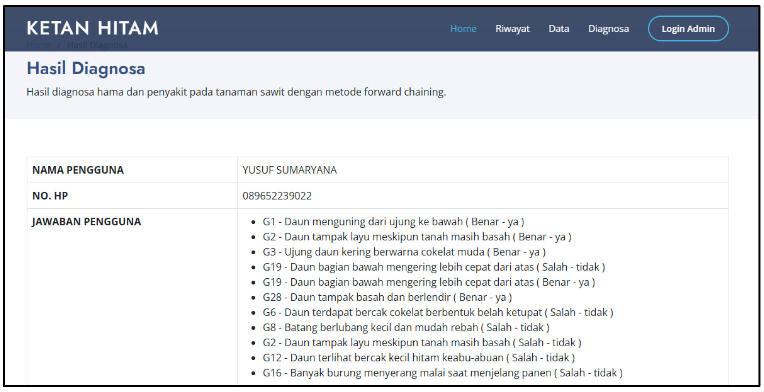

Figure 5. Diagnosis Result Generated by Forward Chaining

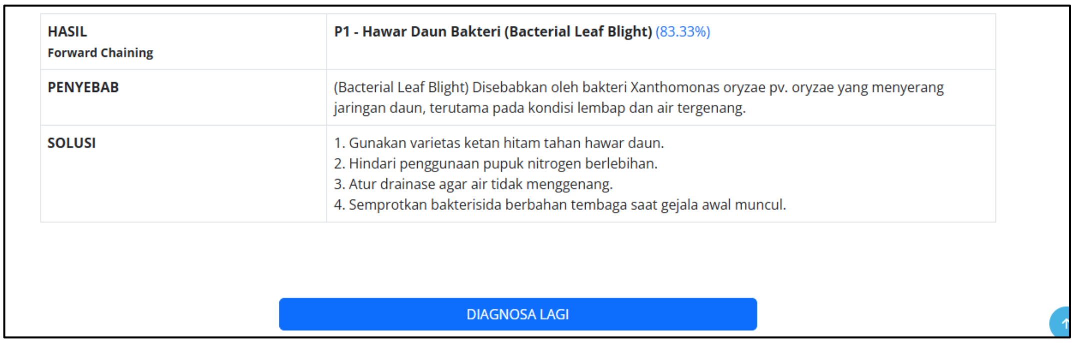

Figure 6. Final Diagnosis Verified by the Hybrid Inference Mechanism

The diagnosis result demonstrates that the proposed hybrid inference mechanism successfully generated a candidate disease using Forward Chaining and confirmed the diagnosis through Backward Chaining verification before presenting treatment recommendations. Unlike conventional Forward Chaining systems, the proposed approach ensures that the inferred diagnosis satisfies the supporting production rules before being accepted as the final diagnosis.

3.2. Discussion

The expert validation results showed that the proposed expert system achieved a diagnostic accuracy of 95%, with 19 out of 20 test cases producing diagnoses consistent with expert assessments. This result indicates that the knowledge base and IF–THEN production rules were able to represent expert reasoning effectively for diagnosing diseases in black glutinous rice plants. The obtained accuracy demonstrates that the proposed rule-based expert system can provide reliable diagnostic recommendations for the evaluated cases.

The integration of Forward Chaining and Backward Chaining contributed to improving the consistency of the reasoning process. In the proposed workflow, Forward Chaining first generated a candidate disease based on the symptoms selected by the user, while Backward

Chaining subsequently verified whether the inferred candidate satisfied the corresponding production rule before confirming the final diagnosis. Unlike conventional Forward Chaining implementations that directly present the inferred result, the additional verification stage reduced the possibility of accepting unsupported diagnoses when multiple diseases exhibited similar symptom patterns.

One test case produced a diagnosis that differed from the expert assessment due to the similarity of symptoms shared by Bacterial Leaf Blight (P01) and Brown Planthopper (P02). Under this condition, several production rules were partially satisfied by the same symptom combination. Nevertheless, the proposed hybrid inference mechanism still generated a relevant candidate disease and verified the diagnosis using the available knowledge base. This finding suggests that the quality of the diagnostic results is strongly influenced by the completeness and consistency of the production rules (Giarratano & Riley 2005).

The findings of this study are consistent with those reported by Honggowibowo (2009), who demonstrated that combining Forward Chaining and Backward Chaining can improve the reliability of rule-based expert systems for agricultural disease diagnosis. However, unlike previous studies that mainly focused on applying both inference methods independently, this study implements a sequential hybrid inference workflow, in which Forward Chaining is dedicated to candidate disease generation and Backward Chaining functions as a verification stage before the diagnosis is confirmed. This sequential reasoning process represents the main contribution of the proposed expert system.

Previous studies have shown that rule-based expert systems remain effective for rice disease diagnosis, including Android-based implementations, web-based systems, and approaches combined with additional reasoning methods (Endra & Antika, 2021; Holifah et al., 2021; Agusniar, 2024; Danga et al., 2025).

Although the proposed system demonstrated promising diagnostic performance, this study has several limitations. The evaluation involved only 20 representative test cases, and the performance assessment relied primarily on diagnostic accuracy and expert agreement. Furthermore, the quality of the inference process remains dependent on the completeness of the knowledge base and the production rules provided by domain experts.

Future research should expand the knowledge base by incorporating additional diseases, symptoms, and environmental factors affecting black glutinous rice cultivation. Moreover, larger validation datasets and additional evaluation metrics, such as precision, recall, and F1-score, should be considered to provide a more comprehensive assessment of the proposed expert system. Integrating uncertainty reasoning methods, such as Certainty Factor or Dempster–Shafer Theory, may also improve diagnostic performance when multiple diseases exhibit overlapping symptoms.

The main contribution of this study lies in the proposed sequential hybrid inference workflow, where Forward Chaining is used for candidate disease generation and Backward Chaining is employed as a verification mechanism before confirming the final diagnosis.

4. CONCLUSION

This study presented a web-based expert system for diagnosing diseases in black glutinous rice plants by integrating Forward Chaining and Backward Chaining within a hybrid inference workflow. The proposed system was developed using the Expert System Development Life Cycle (ESDLC), while expert knowledge was represented through a knowledge base consisting of 30 symptoms, 6 pests and diseases, and IF–THEN production rules. In the proposed inference mechanism, Forward Chaining was employed to generate candidate diseases from user-selected symptoms, whereas Backward Chaining was used as a verification stage before confirming the final diagnosis and presenting treatment recommendations.

The evaluation results demonstrated that the proposed expert system operated correctly in all functional tests and achieved a diagnostic accuracy of 95%, with 19 out of 20 test cases producing diagnoses consistent with expert assessments. These results indicate that the proposed knowledge base and hybrid inference mechanism are capable of representing expert reasoning effectively for the evaluated cases. Compared with conventional rule-based implementations that directly present diagnosis results after Forward Chaining, the proposed approach introduces an additional verification stage using Backward Chaining, thereby improving the consistency of the reasoning process.

Nevertheless, this study has several limitations. The evaluation involved a limited number of representative test cases and relied primarily on expert agreement as the performance measure. Future work should expand the knowledge base by incorporating additional diseases and symptoms, validate the system using larger datasets, and employ additional evaluation metrics such as precision, recall, and F1-score. Furthermore, integrating uncertainty reasoning methods, such as Certainty Factor or Dempster–Shafer Theory, may further improve diagnostic performance in cases involving overlapping disease symptoms.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirm that this manuscript is original, free from plagiarism, and has not been published or submitted for publication in any other journal.

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