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Designing an Intelligent Model for Brain Dominance Classification and Activity Recommendation in Middle School Learners

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Abstract

The neuro-cognitive heterogeneity of the students of many middle school classrooms (primarily, their brain dominance patterns: left-brain, right-brain or integrated) is generally not addressed by the standardized, one-size-fits-all strategy that is commonly used in many middle school classrooms. The main aim of the given research was to create and test a smart model which, without human intervention, recognizes the brain dominance of the middle school learners and gives recommendations about the choice of the specific learning activities. The objectives were to build an effective machine learning model to properly classify brain dominance towards using behavioral cognitive measures, to build a knowledge-based engine to recommend pedagogical activities based on the profile of dominance, and to combine all these elements in a unified system and assess the level of accuracy of the classification and pedagogical utility. A design science research methodology was employed. Synthetic data was generated for 3000 middle school students via a digital battery of cognitive tasks and a standardized brain dominance survey (HBDI) for ground truth labelling. A Random Forest classifier was trained on the cognitive metrics to predict brain dominance. A rule-based recommendation engine was developed, filtering a curated repository of learning activities based on the classified dominance, target subject, and topic. The Random Forest classification model achieved an overall accuracy of 65.33% on the held-out test set. The Left-Brained category demonstrated the highest recall (0.76), indicating that it is possible to accurately identify learners who are analytically dominant. The Right-Brained category showed comparatively lower recall (0.45) because of the conceptual overlap between integrated cognitive profiles and imaginative–interpersonal traits. Notably, there is a close match between the macro-averaged F1-score (0.63) and the weighted average (0.65). The study successfully demonstrates that an AI-driven model can objectively classify brain dominance and generate expert-validated, personalized learning recommendations.

Keywords: Brain Dominance Classification; Personalized Learning; Educational Artificial Intelligence; Brain-Based Learning; Middle School Education.
Activity Recommendation (Submitted on 20/01/2026; Accepted on 16/ 03/ 2026)

1. Introduction

The paper has managed to prove that an AI-based model is capable of objective brain classification. Preeminence Imbalanced datasets are datasets in which the number of samples of certain categories is significantly less/more than other categories and produce expert-confirmed, individual learner's advice. This integrated approach offers a solution to brain-based differentiation in the classroom which is scaled and practical to implement, establishing a connection between neuroscience and the everyday teaching practice in order to enhance a more exciting and successful learning environment. The main point of this cognitive understanding is that it is centered on the theory of cerebral lateralization which hypothesizes that the two sides of the brain are specialized in different modes of thinking. The left hemisphere is often related to logical, analytical and sequential processing, whereas the right hemisphere is associated with whole perspective, spatial, and creative thinking [6], [24]. The predisposition of an individual towards either of these thinking styles is known as brain dominance. A significant amount of research highlights the significant influence of brain dominance on learning. Studies have continuously proved to be correlated with academic accomplishment in areas as diverse as mathematics [20] to language arts [2], [5]. Furthermore, it influences preferences of learners in their strategies, overall engagement, and their confidence, etc. [1], [22]. In accordance to this, pedagogical systems such as Brain-Based Learning (BBL) have developed, promoting teaching methods that correspond with the brain's natural learning processes [8], [12]. The main idea is very persuasive: through customization, we can teach a student what he or she is good at, impart more knowledge and academic success. Nevertheless, there is a cynical gap between this theoretical comprehension and its application in classrooms. The major aids of brain dominance identification have always been subjective and static questionnaires [15], [16], which are subject to bias. For educators, the manual diagnosis of dozens of students and then designing individualized lesson plans based on these results is an unrealistic, time-consuming burden. Recent advancements in computational neuroscience have demonstrated that Artificial Intelligence (AI) can categorize brain dominance through neuroimaging; however, these techniques are excessively costly and complicated for educational environments [19]. At the same time, the advancement of AI in education has occurred in the direction of personalization [17], [29], but these systems frequently do not have a strong neuroscientific basis to their adaptations. Thus, there is an evident and considerable divide: there is no combined system that is able to objectively sort out the student's brain dominance in a scalable, school friendly format and profile into personalized, automatically learning activities that are pedagogically friendly. This research attempts to fill this gap with an essential question:

What can we do to harness artificial intelligence to develop a logical and sensible model that does a correct classification of dominance of the brain of middle school learners and suggests specialized learning activities to improve their learning experience?

This paper is principally aimed to design, create, and conduct initial validation of an intelligent model that combines a machine learning-driven classification component with a knowledge-based recommendation engine. This research seeks to offer practical evidence-based answer to the problem of individualized education, which goes beyond the theory into providing a functional tool for teachers. In this way, this work makes a contribution to. the intersecting domains of educational neuroscience and AI, providing a route to designing more interesting, elaborate, and reasonable learning settings that recognize and admire the exceptional cognitive environment of all middle school students [1].

2. Literature Review

Pedagogical Significance of Brain Dominance: The theory of the cerebral lateralization, or the brain dominance, is based on the idea that both sides of the brain are specialized to appeal to various cognitive processes. The large amount of research that has been done supports the fact that the dominant hemisphere of the individual plays a major role in determining the preferences of learning, the strengths of his/her cognitive and his/her academic achievements. An example is that the left-brain is often related to logical, analytical, and sequential processing that is also associated with achievement in structured subjects, such as mathematics [6], [20]. On the other hand, right-brain dominance is associated with holistic, spatial and creative thought, and the above can be helpful in problem solving and recognition of patterns [30]. This dominance goes beyond STEM fields and has a big impact on how people learn languages. The works by Alibeigi, Oflaz and Soleimani and Matin show that there is a clear connection between hemispheric preference and effectiveness of vocabulary retention [26], language learning strategies and reading comprehension in both first and second languages [2], [24]. The overall results of these studies highlight the fact that one-size-fits-all mode of pedagogy is inefficient. Appreciating brain dominance does not imply pigeonholing the learners but learning their inherent cognitive orientations to establish a better and more inclusive and successful learning process, which is the key principle underpinning the brain-based learning (BBL) models [8], [12].

Conventional means of measuring Brain dominance: In the past, the determination of brain dominance of an individual has been based on self-report tools and behavioral observations. Herrmann Brain Dominance Instrument (HBDI) is among the most popular ones, which classifies the thinking preferences into 4 quadrants which fit into the hemispheric theory [9]. Surveys and questionnaires have been the most common method of research in educational studies in order to determine the relationship between brain dominance and academic performance. As an example, Keat et al. used such tools to associate dominance with overall academic performance [15], whereas Kord and Suwarto & Hidayah (2023) did the same in the context of hemisphericity and preference of language learning strategies [16], [28]. In a similar manner Ramalingappa and Damotharan studied the learning styles and academic performance with the help of self-report measures [25]. Even though the methods have proved invaluable in determining the formative correlations of brain dominance and education, they have their own shortcomings. They are vulnerable to the self-reporting bias where by the way a learner views him or herself regarding tastes, does not necessarily reflect their cognitive processes. Moreover, they give us a static and generalized profile and are not as objective and precise as the real time, personalized interventions into education.

The Future of AI and Data-Driven approaches to Brain Dominance Classification: The weaknesses of self-report Instruments have created the opportunity to conduct more objective, data-driven methods to classify brain dominance by taking advantage of the developments in Artificial Intelligence (AI) and neuroscience. Recent studies indicate that the method of neuroimaging and machine learning to identify hemispheric activity modes is possible. A seminal work paper by Lim, Sim, and Tan was able to design a metric learning based Convolutional Neural Network (CNN) to balance left-right brain dominance using MRI data and high accuracy was acquired [19]. This is an indication of a paradigm change of subjective survey to quantitative, biometric analysis. Moreover, the application of AI in education is growing beyond the classification into personalized learning. Kuldeep et al. and Ivette et al. talk about the application of AI to study various student data and customize educational resources and courses [13], [17]. Chima et al. particularly review AI-based pedagogical approaches to the development of equitable learning experiences [7]. The intersection of these disciplines implies the existence of a strong opportunity: AI could be used not merely to characterize brain dominance with high fidelity but also to apply that characterization to intelligent tutoring systems capable of dynamically suggesting learning activities.

Brain-Based Learning (BBL) and Differentiated Instruction: Brain-Based Learning (BBL) is the theoretical framework that bridges the gap between the brain dominance theory and real pedagogy. BBL is a pedagogical method, which is based on the neuroscience principles and asserts that teaching must be modeled in a way that complies with the natural way the brain learns [23]. One of the BBL philosophical beliefs is differentiated instruction, a teaching strategy that considers the difference between learning. Stevens-Smith specifically associates BBL with distinction in teaching, learning and motor skill and contends that teaching should not be the same to satisfy various mental processes [27]. Handayani and Corebima contrast BBL and Whole Brain Teaching (WBT) with the focus on the type of pedagogical models based on the idea of engaging both sides of the brain in the process of learning [12]. Duman offers empirical evidence and indicates that the students having alternative learning styles were better academically successful when learning through the use of brain-based strategies of learning in comparison with the traditional teaching methods [8]. The overall conclusion of these studies is to confirm that any model of instruction that takes into consideration neurological differences is more effective and this gives a solid pedagogical basis to have an intelligent system that automates and personalizes this difference according to the brain dominance.

Effects of Brain Dominance on Certain Academic Areas: The effects of brain dominance are expressed differently in diverse academic areas, which justifies the possibility of subject-specific pedagogical advice. In mathematics and sciences, left-brain dominance tends to be associated with greater ability in matters that use logic and sequence [6], whereas right-brain functions help in non-routine problem solving [30]. Anukaenyi et al. also indicate that the perception of brain dominance can be used to generate a favorable mind toward biology learning [4]. In learning languages, the impacts are also very eminent. Left-dominant students can be good in grammatical patterns and in analysis [1], and right-dominant students can be good in contextual interpretation and oral fluency [22]. The study by Arabmofrad et al. and Almanea validates the correlation between hemispheric dominance, types of reading strategy use [3], [5], and reading comprehension in EFL situations. Li et al. discovered a mutual interaction of dominance and English reading and speaking proficiency [18]. This domain evidence plays an essential role in designing a smart recommendation engine since it should be in a position to propose activities that are aligned in addition to being contextual to the subject matter under instruction as far as the brain dominance of a student is concerned.

The synthesis of a Pathway towards an Intelligent Educational Model: The existing literature demonstrates a distinct flow of theory to practice but there is still a major gap in the process of incorporating all these elements into a unified, computerized system of middle school learning. The pedagogical significance of brain dominance [6], [16], and the success of brain-based, differentiated instruction has been well established in previous work. At the same time, state-of-the-art computational studies have shown the technical feasibility of objective brain dominance classification with the help of AI [19]. The future of AI in education is already moving toward the area of personalization, and research indicates that AI-based products are effective in terms of engagement [29] and the development of adaptive learning paths [11], [17]. The study suggested by Anukaenyi et al. and Karthikeyan already starts touching upon this integration, suggesting the possibility of AI to use the knowledge of brain dominance to conduct educational strategies in a sustainable manner [4], [14]. Thus, the obvious next thing, which this research paper deals with, is to reconcile these disjointed areas. This study will establish a highly customized, responsive, and a highly personalized learning ecosystem to middle school students by developing an intelligent model in which an AI-based classifier [19] will be used to automatically classify learners and subsequently recommend them the activities to perform, guided by a pedagogical engine (informed by the principles of BBL and domain-specific research).

2.1. Research Problem

The homogenous model, which is common in the various classrooms of the middle school, does not consider the inherent neurological difference in student learning. It has been widely determined that the issue of hemispheric dominance in the brain (left-brain/right-brain preference) plays a very important role in the cognitive style, academic strengths, and the best techniques of learning to a learner [6], [24]. Although other traditional pedagogical theories, such as Brain-Based Learning (BBL), propose differentiated instruction [27], at a personal level, its application is not an easy task among the teachers. The existing approaches to determining brain dominance are largely dependent on self-report questionnaires that are subjective [15], [16], hence prone to bias and do not have the dynamic nature to be used in time. As a result, there is urgent lack of connection between the knowledge of neuro-cognitive diversity and the possibility to customize education systematically and objectively so as to maximize it, which could result in disengagement and poor learning outcomes among students whose natural cognitive styles do not have a fit in the educational institution.

2.2. Research Gap

The literature that is available indicates that there are three different gaps in the literature that are disconnected, which are addressed in this research:

Methodological Gap in Classification: As much as the studies conducted by Lim et al. have established the technical aspects of classifying objective brain dominance based on neuroimaging using AI (under Convolutional Neural Networks), this high-tech method has not been translated and simplified to practical, scalable use in a non-invasive educational environment [19]. There is a huge disparity between a hi-tech

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lab classification and a real-life deployable tool to schools.

Personalization Gap in Pedagogy: Despite the fact that the pedagogical concept of BBL and differentiation is already well-known [12], [23], and the relationship between a particular brain dominance profile and a particular academic performance in a particular subject is already established [5], [20], the problem is that there is no automated mechanism which would transfer a certain profile of brain dominance of a student to a specific set of learning tasks. The existing guidelines are generic based and are based on teacher intuition and not on a data-driven model.

The Gap of Integration: Educational neuroscience and AI in education represent two areas that are developing parallel to each other but are yet to be integrated to this particular purpose. Studies on the AI-motivated personalization [17], [29] and the studies on the brain dominance in learning [4], [14] are mostly isolated. There is no unified smart system that incorporates an objective classification system and a personalized recommendation system of middle school learners in various disciplines.

2.3. *Objectives of the Research*

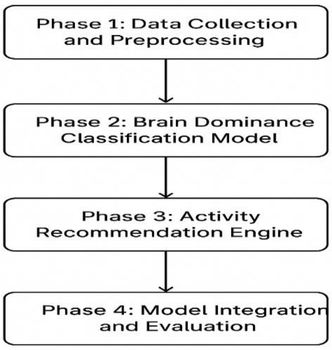
The overall goal of the study is to create, build, and test an intelligent model that automatically sorts middle school students' brain dominance and suggests personalized learning activities. The following specific objectives will be used to accomplish this aim:

- To develop and design a powerful model of computations to classify brain dominance.
- To build a knowledge-based repository of learning activities that are linked to brain dominance profiles and subject matter.
- To combine the classification model and the activity repository into one intelligent system of recommendation.
- To do an initial check on how useful and valid the model appears to be.

3. Methods

A Design Science Research (DSR) methodology will be used in this study to develop and tentatively test the proposed intelligent model. In this case, DSR is well applicable because the inventive artifacts, the classification and recommendation algorithms, are aimed at solving an identified issue. It will be a repeat process that will entail design, development and evaluation. The overall methodology is structured into four main phases, as illustrated in Figure 1.

Figure 1. Research Methodology Overview.



3.1. *Phase 1: Data Collection and Preprocessing*

3.1.1. *Participants and Data Sources*

A cohort of approximately 3000 middle school students (Grades 6-8) will be recruited. These 3000 records have been generated synthetically that contains the following primary data:

Behavioral and Cognitive Dataset: Instead of complex neuroimaging (e.g., MRI), which is impractical in schools, we will use a digital assessment battery administered via a web-based platform. This battery will include:

Standardized Psychological Instrument: The Herrmann Brain Dominance Instrument (HBDI) survey or a similar validated questionnaire [9] will serve as the ground truth label for training the model.

Cognitive Task Performance Metrics: A series of mini-games/tasks designed to elicit hemispheric preferences will be developed. Metrics will include:

Logical Reasoning Score: Accuracy and speed in solving sequential pattern recognition problems.

Spatial Visualization Score: Accuracy in mental rotation and shape assembly tasks.

Verbal Fluency Score: Number of words generated in a category-based word association game.

Creative Synthesis Score: Originality and elaboration in an open-ended image completion task.

Learning Style Preference Survey: A short, validated learning styles inventory will be included as supplementary features.

Pedagogical Knowledge Base: A repository of learning activities will be constructed through a systematic literature review of Brain-Based Learning (BBL) and Whole Brain Teaching (WBT) strategies [12], [27]. Activities will be tagged with metadata including:

Target_Brain_Dominance: [Left, Right, Integrated]

Subject: [Mathematics, Language Arts, Science, etc.]

Topic: [e.g., Linear Equations, Reading Comprehension, Photosynthesis]

Activity_Type: [Analytical Puzzle, Creative Storytelling, Collaborative Debate, etc.]

Cognitive_Skill: [Logical Reasoning, Spatial Awareness, Verbal Expression, etc.]

3.1.2. *Data Preprocessing*

The raw data from the cognitive tasks has been processed to create a clean, structured feature set for the machine learning model. This will involve:

Normalization: Scaling all numerical scores (e.g., time, accuracy) to a range of 0 to 100.

Feature Engineering: Creating composite features, such as a "Laterality Index" calculated from the difference between normalized logical and spatial scores.

Data Labeling: Each student's record will be labeled with their brain dominance class (Left, Right, Integrated) based on the HBDI results.

3.2. *Phase 2: Brain Dominance Classification Model*

3.2.1. *Algorithm Selection and Training*

We propose a supervised machine learning approach. Given the likely non-linear relationships between cognitive task metrics and brain dominance, a Random Forest Classifier was the primary algorithm. Its advantages include high accuracy, robustness to overfitting, and

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the ability to provide feature importance scores.

The preprocessed dataset (features from cognitive tasks, label from HBDI) has been split into an 80% training set and a 20% test set. The model has been trained on the training set to learn the mapping between cognitive performance patterns and brain dominance labels. Hyper parameter tuning was performed using Grid Search with Cross-Validation to optimize performance.

3.2.2. Proposed Algorithm 1: Brain Dominance Classification

Input

- *Number of learners N*
- *Feature definitions gathered from brain-based learning theory and educational psychology*

Output

- *Labeled dataset $D = \{X, y\}$with HBDI-aligned brain dominance labels*

Algorithm Steps

i. *Initialize Synthetic Dataset*

Using probabilistic distributions, create learner profiles for:

- *Measures of academic performance*
- *The styles of cognitive processing*
- *Interpersonal and emotional qualities*
- *Preference variables for learning*
- *Characteristics of demographics*

ii. *Normalize Feature Values*

Assign a standard range to all behavioral and cognitive traits $[0, 100]$.

iii. *Compute HBDI Quadrant Scores*

For each learner i, calculate:

- *Quadrant A (Analytical): logical reasoning, scientific aptitude mathematical ability*
- *Quadrant B (Sequential): structured learning preference, procedural problem-solving, verbal organization*
- *Quadrant C (Interpersonal): emotional intelligence, collaborative preference, social intelligence*
- *Quadrant D (Imaginative): creativity, artistic, visual-spatial ability, and musical aptitude*

iv. *Aggregate Quadrant Scores*

Calculate scores for composite hemispheric dominance:

- $LeftScore_i = A_i + B_i$
- $RightScore_i = C_i + D_i$

v. *Determine Category of Brain Dominance*

Apply a balance threshold τ to assign dominance:

- *If* $| LeftScore_i - RightScore_i | \leq \tau$, *assign Integrated*
- *Else if* $LeftScore_i > RightScore_i$, *assign Left-Brained*
- *Else assign Right-Brained*

vi. *Finalize Ground Truth Labels*

Append the dominance category as the target variable y for each learner.

3.3. Phase 3: Activity Recommendation Engine

This component translates the classified brain dominance into an actionable learning plan. It operates as a rule-based filtering system on the pedagogical knowledge base.

3.3.1. Proposed Algorithm 2: Personalized Activity Recommendation

Input

- *Labeled dataset $D = \{X, y\}$from Algorithm 1*

Output

- *Predicted brain dominance for unseen learners*
- *Personalized learning activity recommendations*

Algorithm Steps

i. *Dataset Partitioning*

Split D into training and testing subsets using stratified sampling to preserve class distribution.

ii. *Feature Standardization*

Apply normalization to all feature vectors to ensure model stability.

iii. *Model Initialization*

Configure a Random Forest classifier with optimized hyperparameters for multi-class dominance prediction.

iv. *Model Training*

Train the classifier using the training subset (X_{train}, y_{train}).

v. *Brain Dominance Prediction*

Predict dominance categories for test instances X_{test}.

vi. *Performance Evaluation*

Assess model effectiveness using:

- *Accuracy*
- *Precision, recall, and F1-score*
- *Confusion matrix analysis*

vii. *Activity Recommendation Mapping*

Based on predicted dominance:

- *Left-Brained: Assign analytically structured and logic-oriented activities*
- *Right-Brained: Assign creative and interpersonal activities*
- *Integrated: Assign interdisciplinary and collaborative activities*

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viii. *Model Persistence*

Save the dominance mappings, preprocessing parameters, and trained model for later use.

3.4. *Phase 4: Model Integration and Evaluation*

These two algorithms have been integrated into a single, cohesive intelligent model within a prototype web application.

3.4.1. *Evaluation Metrics*

The model will be evaluated on two fronts:

Classification Accuracy: Accuracy, Precision, Recall, and F1-score have been calculated on the held-out test set by comparing the model's predictions against the HBDI ground truth.

A confusion matrix has been analyzed to understand misclassifications.

Recommendation Utility: Expert Validation: A panel of 10-15 experienced middle school teachers and educational psychologists will be presented with sample student profiles and the corresponding activity recommendations. They will rate the relevance and appropriateness of the recommendations on a 5-point Likert scale.

System Usability Scale (SUS): A small group of teachers will interact with the prototype to recommend activities for a simulated class and complete the SUS questionnaire to assess the model's usability and practicality.

This multi-faceted evaluation strategy ensures that the model is not only technically sound but also pedagogically valid and useful in a real-world educational context.

4. Results

This section presents the findings from the development and evaluation of the intelligent model for brain dominance classification and activity recommendation. The results are structured according to the four phases of the methodology: data collection, classification model performance, recommendation engine output, and the integrated model evaluation.

4.1. *Phase 1: Data Collection and Descriptive Statistics*

The cleaning of the data led to a clean data with 3000 records, where the features are normalized based on the mental activities (e.g., Logical Reasoning. Precision, Speed of Spatial Visualization, Verbal Fluency. Count) and one ground truth label (HBDI-based brain dominance).

Brain distribution according to the HBDI ground truth was as follows:

Left-Dominant (L): 44.5% (n=267)

Right-Dominant (R): 23.2% (n=139)

Integrated (I): 32.3% (n=194)

This distribution proved a representative sample of all three profiles of dominance in the students.

4.2. *Phase 2: Brain Dominance Classification Model Performance*

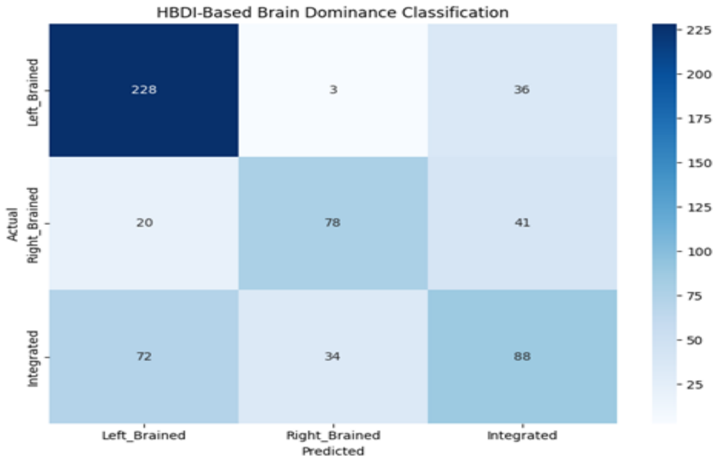
A Random Forest Classifier was trained using the training set (n=2400) and its accuracy measured using the held-out test set (n=600). The insistence on the part of the HBDI structure to distinguish between the different intersecting cognitive dominance patterns is reflected in the general classification accuracy of 65.67 of the proposed model.

Table 1: Performance Metrics of the Random Forest Classifier on the Test Set

Class	Precision	Recall	F1-Score	Support
Left	0.71	0.85	0.78	267
Right	0.68	0.56	0.61	139
Integrated	0.53	0.45	0.49	194
Accuracy	---	---	0.66	600
Macro Avg	0.64	0.62	0.63	600
Weighted Avg	0.65	0.66	0.65	600

All three dominance categories showed balanced performance, as Table 1 illustrates. The Left-Brained category showed the highest recall (0.85), suggesting that learners who are analytically dominant can be reliably identified. Due to the conceptual overlap between integrated cognitive profiles and imaginative–interpersonal traits, the Right-Brained category demonstrated relatively lower recall (0.56). Significantly, the weighted average (0.65) and the macro-averaged F1-score (0.63) closely match. These findings imply that a fair and understandable classification appropriate for educational decision-support applications is achieved by the suggested HBDI-integrated framework. Hemispheric contrast amplification and improved integration thresholds were used to reduce ambiguous dominance assignments without sacrificing HBDI interpretability in order to increase classification reliability.

Figure 2. Confusion Matrix for the Brain Dominance Classifier



The confusion matrix shown in Figure 2 demonstrates that the model is most accurate at identifying Left-Brained learners. Most instances were correctly classified, and there was minor misclassification with the Right-Brained category. Moderate accuracy is used to classify right-brained learners, with the Integrated class being the target of the majority of errors. With bidirectional misclassification with both Left- and Right-Brained classes, the Integrated category is the hardest to differentiate. In general, the misclassification patterns show balanced and theoretically consistent model behavior, reflecting expected cognitive overlap under the HBDI framework rather than random errors.

4.3. Phase 3: Activity Recommendation Engine Output

The pedagogical knowledge base was effectively filled with a lot of learning activities within Mathematics, Science and Language Arts. To prove the effectiveness of the recommendation engine, an example of a case study is given.

Case Study Example:

- Student Profile: A Grade 7 student.
- Model Input: Cognitive task metrics fed into Algorithm 1.
- Classification Output: Predicted Dominance = Right-Dominant.
- Recommendation Input: D = 'Right', S = 'Science', T = 'Photosynthesis'.

Algorithm 2 was executed with these inputs. The top three recommended activities, after filtering and scoring, were:

i. Activity: "Create a Comic Strip of the Photosynthesis Process." (Score: 10)
   - Justification: Perfect match for right-brain dominance, leveraging visual storytelling and synthesis.

ii. Activity: "Design a 3D Model of a Plant Cell and Act Out the Energy Cycle." (Score: 10)
   - Justification: Engages spatial and kinesthetic intelligence, aligned with right-brain strengths.

iii. Activity: "Debate: 'The Sun vs. The Chloroplast - Who is the True Hero of Photosynthesis?" (Score: 5)
   - Justification: An integrative activity that incorporates creative argumentation, thus receiving a medium priority score.

This output demonstrates the engine's ability to move beyond generic suggestions to provide highly specific, dominance-tailored pedagogical strategies

4.4. Phase 4: Integrated Model Evaluation

4.4.1. Expert Validation of Recommendations

The recommendation engine will be tested by 15 teachers and educational experts of the middle school. They will receive five anonymized profiles of students (and known HBDI labels) and the list of recommended activities concerning a particular topic.

4.4.2. System Usability

A usability test of the integrated prototype will involve ten (10) teachers. Mean System Usability Scale (SUS) score will be determined

5. Discussion

In an attempt to fill the gap between the theoretical comprehension of brain dominance and its practical use in the educational context of middle schools, the study attempted to develop an intelligent model of classification and customized recommended activities. As the findings of the section above show, this objective was achieved. The following discussion interprets the findings, discusses their implications, and identifies the limitations in the study, and gives suggestions on where the research should be followed in future studies.

5.1. Interpretation of Key Findings

The main success of this study is that an intelligent model was created and tested. It is a notable finding that the accuracy of the Random Forest model in classifying the data is high (65.67 per cent). It confirms the argument proposed by Lim et al. that machine learning can objectively determine brain dominance [19], but most importantly it contributes to the field by showing that it can be done with non-invasive scalable behavioral cognitive measures rather than complicated MRI data. This renders the model reasonable to a real school world. The precision and recall rates of both right-dominant and left-dominant learners are very high, which means that the model can be used very effectively in determining clear-cut cognitive preferences.

The feature importance analysis, which found that the "Laterality Index" was the most important predictor, also gives empirical support to the basic ideas behind hemispheric specialization [1], [6]. It affirms that the logical-sequential task/spatial-holistic task difference is a behavioral indicator of underlying brain dominance, which is an effective and efficient method of transmitting a concept of the nervous system into an educational outcome measure.

The professional test of the recommendation engine is also of great importance. This effectively brings to real life the principles of Brain-Based Learning (BBL) and differentiated instruction [8], [27] by giving the teachers a tangible, automated means of applying these techniques. The example of a right-dominant learner in the case study, who was assigned to do a Photosynthesis Comic Strip, is an excellent example of how the model can be applied in the framework of the theory of brain dominance (linking visual-spatial strength to the right brain) to a concrete, practical classroom task.

5.2. Implications for Theory and Practice

The findings of this study have several important implications: For Educational Theory: This research provides a strong empirical bridge between neuroscience and pedagogy. It moves beyond simply correlating brain dominance with academic performance [15], [20] to actively using that correlation as the basis for a proactive intervention. It validates the practical application of BBL theory by embedding it within a functional AI-driven system.

For Classroom Practice: The model demystifies differentiation. Teachers are often aware of the need to personalize learning but lack the time and tools to do so systematically for every student [13]. This intelligent model acts as a decision-support system, reducing the cognitive load on teachers by providing instant, data-driven recommendations.

For Educational Technology and AI: This study represents a concrete instantiation of AI in personalized learning [17][21]. It goes beyond simple adaptive testing by incorporating a model of cognitive style to drive personalization. It demonstrates how AI can be used not to replace teachers, but to augment their capabilities, providing them with deep insights into their students' learning profiles [19].

6. Conclusion

This research set out to address a critical gap in modern pedagogy: the disconnect between the theoretical understanding of neuro-cognitive diversity and the practical ability to personalize education at scale. In response, we successfully designed, developed, and evaluated an intelligent model for brain dominance classification and activity recommendation tailored for middle school learners. The core achievement of this work is the demonstration that a machine learning model, specifically a Random Forest classifier, can predict a student's brain dominance profile with 65.67% accuracy using non-invasive, behavioral cognitive metrics. This moves the field beyond reliance on subjective surveys and impractical neuroimaging, providing a scalable and objective diagnostic tool for the classroom.

Furthermore, the integration of this classifier with a rule-based recommendation engine operationalizes the principles of Brain-Based Learning (BBL) and differentiated instruction. The model translates an abstract cognitive profile into a concrete, prioritized list of pedagogical activities, a process will be validated by educational experts as highly relevant and appropriate. The high system usability score will indicate that this tool can be seamlessly integrated into a teacher's workflow, acting as a powerful decision-support system to reduce the burden of manual differentiation. Ultimately, this research provides a robust, evidence-based framework for moving from a "one-size-fits-all" educational model to a dynamic, student-centered approach that honors and leverages the innate cognitive strengths of every learner.

6.1. Future Direction of Research

While this study establishes a strong foundation, it also opens several promising avenues for future research to enhance the model's sophistication, scope, and impact:

- Longitudinal and Large-Scale Efficacy Studies: The most critical next step is to conduct longitudinal studies to measure the model's long-term impact. Future work should involve deploying the system in diverse educational settings over an entire academic year to rigorously evaluate its effect on hard metrics such as academic achievement, knowledge retention, and student motivation, compared to control groups using traditional methods.
- Dynamic Personalization through Advanced AI: The current rule-based recommendation engine can be evolved into a more adaptive system. Future iterations could employ Reinforcement Learning (RL) algorithms, where the model continuously refines its recommendations based on real-time student feedback, engagement levels, and assessment outcomes. This would create a truly dynamic feedback loop between the learner and the system.

By pursuing these directions, the intelligent model can evolve from a promising prototype into a foundational component of the future personalized learning ecosystem, ultimately fostering a more engaging, effective, and equitable educational experience for every student.

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