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ORIGINAL CONTRIBUTION

Using Novel Multi-Piece Tangram as a Manipulating Tool for STEAM Curriculum Design: An Optimization-Based Experimental Approach to Aesthetic Education

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Abstract— It has also been noted that the literature is scarce on the inclusion of aesthetic education under the STEAM framework. To address this gap, this study proposes an optimized model titled T-STEM-ICA-SVMAP, which includes the integration of Support Vector Machine-based Aesthetic Perception (SVMAP) and the Imperialist Competitive Algorithm (ICA). This study aims to improve the cognitive process of learning and aesthetic perception under the STEAM framework. This study has utilized an experimental study design with four specific research questions: optimization methods, identification of aesthetic components, comparative study of the proposed model, and evaluation of the reproducibility of the system. This study has utilized the publicly available Tangram image dataset available on the Kaggle platform, which includes diverse representations of tangram images. An 80:20 train-test split is applied. Features extracted with SVMAP for visual and geometry, while dynamic curriculum parameters of ICA for the difficulty of the task, geometry restrictions, and activity sequence. The framework was compared with two baseline models: a traditional SVM and a CNN-based classifier. The results show that the proposed framework achieved an accuracy of 0.89, precision of 0.88, recall of 0.87, and F1-score of 0.87, outperforming the two baselines by 0.05–0.11 in all metrics. The findings indicate that combining optimization-driven curriculum design with machine learning-based aesthetic evaluation provides an effective, objective, and reproducible means of integrating aesthetic education into tangram-based STEAM learning. This study contributes a replicable computational-pedagogical pipeline to educational technology and STEAM curriculum research.

Index Terms— Tangram-based STEM education, Imperialist competitive algorithm, Support vector machine, Aesthetic perception, Curriculum optimization, STEAM learning, Image classification

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Introduction

Recent changes to education have created the need for a centralized approach to STEAM subjects, which stands for Science, Technology, Engineering, Arts, and Math. These changes primarily focus on the skills that add value to learning. This is why Montés et al. (2023) proposed an approach to create STEAM projects based on the national curriculum. They suggested that it was very important for projects that combine different topics to match learning goals. In this way, their study shows that for STEAM to work, the tasks and the way they are taught need to

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be changed so that clear connections are made between conceptual knowledge, problem-solving, and creativity. In this regard, the proposed framework allows for the inclusion of active learning tools, manipulatives, and puzzles that can bring the principles of STEAM to life in classroom practices.

The tangram, one of the traditional geometric puzzles, has been well-known, but it has become one of the resurgent themes in recent years regarding puzzles within modern mathematical education. Activity with tangrams offers a manipulable resource through which transitions between two-dimensional and three-dimensional views of geometry may be supported; Kmetová and Nagyová Lehocká (2021) first outlined this potential. The tangram pieces appear to provide an opportunity for hands-on activities that help develop spatial reasoning through visualization of transformations, relationships, and structures. This type of connection between abstract geometric concepts and hands-on activities is similar to one of the main goals of STEAM: To help people improve their spatial thinking and integrative reasoning skills.

The enduring educational potential of tangrams has been elaborated by Santos (2024). He claimed that this riddle was an artifact from the bygone era that keeps acquiring new meanings. The paper argues that tangrams develop problem-solving skills, creativity, and learner engagement from almost any age. Moreover, these resources do not lose flexibility for digital and interdisciplinary learning contexts.

Santos (2024) argued that tangle grams are relevant resources that can connect old-fashioned views of mathematical thinking and new, more STEAM-oriented pedagogies through placing them in modern learning spaces. Generally, evidence has emerged regarding the use of physical manipulatives in promoting children's learning and development. Indeed, Byrne et al. (2023) carried out a very wide-ranging scoping review of various interventions involving physical manipulatives and found benefits generally across cognitive, spatial, and academic domains. Indeed, the review draws attention to the fact that manipulatives yield more potent effects when embedded into highly structured learning activities that make exploration and reflection more likely. Emerging evidence further strengthens such justifications for including puzzle-based manipulatives, such as tangrams, within mathematics and broader STEAM education as a means for promoting active learning.

The developmental foundations of spatial reasoning support the use of manipulatives in early education. Bower et al. (2020) found evidence longitudinally linking early block-building complexity in three-year-olds to later spatial and mathematical abilities. The findings suggest that early involvement in construction and spatial manipulation activities has long-term benefits for mathematical development, justifying the early introduction of spatial puzzles in the curriculum to foster STEAM competencies.

Puzzle-based tasks, besides contributing to cognitive development, are an open window for assessing and nurturing the notion of creativity. Indeed, Ramaraj and Nagammal (2020) put forth a framework for open-ended puzzle task-related assessments, focusing on emergent outcomes rather than pre-specified solutions. This work by them emphasized that puzzles invoke divergent thinking, and the ability to think originally and use various problem-solving approaches is understandably part of a central STEAM educational perspective wherein creativity is also considered a crucial competency.

However, the actual potentials of spatial and puzzle-based learning are noticeably captured only in the feature of a teacher's expertise and professional development. To this end, Bufasi et al. (2024) studied the lesson study as a professional development model for teaching spatial ability within primary STEM contexts. Their findings indicate that collaborative planning, observation, and reflection allow teachers to insert activities of spatial reasoning more seamlessly into their instruction. This is a much-needed dimension of this professional learning to ensure that the purpose and the use of manipulatives and puzzles are not at all superficial.

In this respect, complementary contributions come from Klapwijk et al. (2024), who elaborated modules for professional development on spatial thinking in STEAM education. This work stresses teacher training in terms of explicit links between theory, practice in the classroom, and curriculum design. In this sense, the developed workshops will significantly improve the effectiveness of classroom teaching with tangrams and other manipulatives.

Adams et al. (2023) investigated whether such spatial training transfers to improved achievement in measurement and geometry at the secondary level. The results point out that targeted spatial interventions can indeed positively influence mathematical performance, although transfer generally hinges on task alignment in the instructional design. Strong evidence supports the claim that spatial learning activities yield formal mathematical outcome enhancements if well-designed interweaving occurs at various educational levels.

Finally, computational and artificial intelligence approaches are developing a new frame of view on the time-honoured puzzles. Yamada et al. (2024) addressed tangram puzzles from the viewpoint of generative approaches to solving them; thus, they showed how computational models can generate and extend problematic human strategies. This shows that there is interest in exploring the possibilities of tangram puzzles in the STEAM fields. STEAM fields combine mathematics and computation and artificial intelligence, and perhaps shine the brightest. This series of studies provides a foundation for exploring the possibilities of tangram-based approaches to the STEAM fields.

The references are many, but the argumentation is choppy and has gaps. This makes the sentences like any other. The dialogue changes quickly from spatial reasoning to traditional culture to innovative education without any theory to tie all of these subjects together. Furthermore, there are no research questions and hypothesis statements in the introduction. This is important too. In addition, there are many statements about creativity, psychological healing, and cognitive enhancement without much theory to support these statements. In order to make the introduction more effective, I believe that the authors should discuss what gap in the study of STEAM education this study is filling, how Tangram-based aesthetic education compares to other educational practices that are currently in place, and what kind of theory and practice in education this new curriculum will bring.

Problem statement

Though there is a growing use of geometry-based tangram activities for STEAM learning, there exists a huge identified information gap with regard to aesthetic engagement and its measurement using systematic reference points, and its integration into the learning curricula. Learning methodologies based on tangram activities that are currently used are qualitative and based on static learning sequences, without using objective learning methods for aesthetic perception and dynamic learning mechanisms for improving the quality of learning. Though there is effective use of computational learning methods for solving tangram puzzles for artificial intelligence applications (Yamada et al., 2024), this needs to be explored for improving the learning curricula. Therefore, this study has attempted to bridge this gap by integrating machine learning-based aesthetic evaluation and optimization learning algorithms for improving the learning curricula.

Significance of the study

This research study is important for several reasons. Taking into consideration all the factors mentioned above, it is clear that the main driver behind the evolution of the STEAM curriculum worldwide has been the need for developing aesthetic literacy and creatively interacting with the environment. The proposed framework is based on its features of being replicated and data-driven, as it considers the teachers' need for designing tangram-based educational activities, which are both pedagogically effective and computationally correct. The call for machine learning based analysis for curriculum development is yet another area highlighted by the studies related to computational aesthetics, optimization, and STEAM. So, considering all the factors above, it will not be far from the truth to say that this present study makes a meaningful contribution to the overall field of STEAM curriculum.

Research objectives and questions

In accordance with the discovered research gaps and the above importance, the goals of this research are as follows:

- The aim is to invent a new, distinct, multi-piece tangram-based STEAM curriculum framework for computational optimization and aesthetic education.
- To implement the Imperialist Competitive Algorithm (ICA) for dynamic optimization of curriculum parameters such as task difficulty, geometric constraints, and activity sequencing.
- This research aims to devise and realize a Support Vector Machine-based Aesthetic Perception (SVMAP) model for objective assessment of visual harmony and structural balance of tangram patterns.
- This research aims to test the efficiency of the introduced T-STEM-ICA-SVMAP framework with the baseline models, applying some of the standard classification metrics.
- To show the replicability and verifiability of the approach proposed in this paper, a tangram dataset is publicly available.

To achieve these objectives, the study will follow the research questions:

- RQ1: What is the extent of enhancement of optimizing curriculum parameters for tangram-based STEAM learning by integrating an optimized ICA-based strategy as compared to the non-optimized approach?
- RQ2: How well does the SVMAP model capture and evaluate aesthetic perception features in tangram pattern classification?
- RQ3: Is the proposed T-STEM-ICA-SVMAP framework superior to the baseline CNN and conventional SVM models in accuracy, precision, recall, and F1-score?
- RQ4: In what ways can ML-based aesthetic evaluation results support meaningful integration in a reproducible data-driven STEAM curriculum design framework?

Contribution of the study

This study examines the impact of integrated STEAM education on students' spatial skills, focusing on a narrative-based curriculum in architecture at the university level. The Imperialist Competitive Algorithm (ICA) is presented as an optimization mechanism to contribute to curriculum design through progressive grading of task difficulty and sequencing. The lack of measurable aesthetic assessment in STEAM education was addressed by employing a Support Vector Machine-Based Aesthetic Perception (SVMAP) model as an evaluative tool. In this paper, the model was used to quantitatively assess the visual harmony and structural balance of tangram patterns. These results further show the effective use of publicly available tangram datasets for reproducibility. Overall, the study proposes a hybrid educational-computational framework that connects STEAM pedagogy with AI-based analysis.

Related Work

Multiple studies have recognized that tangrams can be a great teaching tool to enhance children's mental, spatial, and creative abilities. Still, a close examination of these studies shows significant differences in terms of what, how, and who have been covered. Such differences even led to this current research study. A few researchers have written about the educational value of tangram activities, but their studies differ quite a lot in terms of their levels of empirical rigor, their population foci, and their extent of generalizability or translatability into a direct/codified curriculum.

Design-based approaches, such as those studied in Ortiz-Laso et al. (2023), aim to develop mathematical competencies through a project-based learning cycle. In contrast, manipulation-centered interventions, such as those examined in Byrne et al. (2023), are evaluated through observational or quasi-experimental methods and mainly depend on structured hands-on activities. According to İleri et al. (2023), art-integrated pedagogy typically applies developmental psychology frameworks with mixed-method evaluation designs. Conversely, Yamada et al.'s computational models of tangram-based learning from 2024 and 2025 employ adversarial and generative network models, but they are unrelated to the classroom.

Andinasari et al. (2020) explored the role of tangrams in teaching proportional reasoning. Their study on teaching strategies revealed that tangram-based exercises linking abstract numerical relationships with visual and spatial representations could be a helpful tool in enhancing students' grasp of ratio and proportion. Besides, tangrams are not limited to the recognition of shapes; therefore, educationally, their use can be aligned with the ideas of constructive thinking. Moreover, it is instrumental in the genesis of mathematical notions.

Recently, AI has often been the driving force behind tangram studies, advancing beyond present capabilities. For example, Yamada et al. (2025) developed TANGAN, a system based on generative adversarial networks, which solves tangram puzzles. Their paper proves that machines are not only performing calculations but also doing complex spatial reasoning and producing correct puzzle solutions. Although tangram problems are primarily considered an AI domain, they serve to demonstrate just how profound and diverse tangram examination can be. That is why these puzzles represent a very good measuring tool for problem-solving in STEAM, both for humans and machines.

Bofferding and Aqazade (2023) have examined how the structure of tangram puzzles improves students' understanding of geometric transformations. Their classroom study revealed that using students to build target shapes helps them think about congruence, rotation, reflection, and scale. They proposed that composition challenges require students to express geometric relationships, and providing tangram exercises is an effective method for developing spatial language and mathematical communication. However, this study was limited to observational classroom data and did not propose a scalable or computationally replicable framework for assessing spatial reasoning outcomes.

So far, teacher development and instructional practice remain salient elements in achieving the promise that such activities hold. In this regard, Ortiz-Laso et al. (2023) studied the development of teachers to exploit mathematical competencies through STEAM projects. Findings revealed that long-term engagement in interdisciplinary project-based learning equipped teachers with better recognition and exploitation of the competencies identified—spatial reasoning, problem solving, and creativity. This work further substantiates the need for teacher agency and reflective practice when implementing manipulative- and puzzle-based learning in STEAM contexts. Nevertheless, the review does not differentiate between manipulative types or provide optimization criteria for selecting and sequencing manipulative tasks within a structured curriculum.

Research on classroom interventions has supported the educational value of tangram-based media. Diandini et al. (2025) researched the study of tangram-based puzzle media on the learning interest and creative thinking of primary school students. According to their findings, the tangram activities improve students' conceptions and motivation and engagement in learning quite dramatically for both affective and cognitive outcomes. The results relate strongly to primary schooling, which places effective learning at the intersection of maintaining interest and creative ability. Although these findings are promising, they relied on self-reported measures only. Further, there was no computational mechanism that could objectively evaluate the aesthetic or structural quality of student outputs.

Beyond tangram-specific studies, a more general competency discussion is progressing, which adds an important conceptual background to the current work. Mathematical competencies are linked to tangible objects. The work of Cevikbas et al. (2022) does not focus on manipulatives; however, it investigates mathematical modelling competency and provides a systematic literature review of current approaches to conceptualizing, measuring, and providing instructional support. From this perspective, tangram-based and puzzle-oriented tasks might be seen as complementary tools supporting modelling-related competencies by requiring learners to interpret, represent, and solve spatial problems.

In algebraic and computational thinking, Mansoor et al. (2025), Rubbani et al. (2024), and Sarmasági et al. (2025) explored this K-12 student development path. The work foresees a greater appreciation of computational thinking in mathematics pedagogy, where problem-solving is increasingly encompassing logical reasoning, pattern recognition, and abstraction. Such tangram puzzles neatly fall into this new area of educational focus, especially if extended into the digital and algorithmic domain.

Collectively, the reviewed literature confirms the educational potential of tangram-related activities while at the same time highlighting several key limitations. First, most literature has been conducted within limited empirical contexts. Second, although considerable advances have been achieved within the realm of computational tangram puzzles (Rahman et al., 2024; Yamada et al., 2024, 2025), this literature has been conducted without any consideration for educational applications. Third, although aesthetic education has been included as a dimension within

STEAM learning, this has been done without any consideration for quantification or optimization. Finally, although numerous frameworks have been developed for algorithmic optimization of educational curricula as well as machine learning-based evaluation, none have been done within a unified educational setting. This study directly addresses these limitations through the development of the T-STEM-ICA-SVMAP framework.

The research presented in Table I collectively emphasizes three major gaps: the lack of objective aesthetic measurement methods in education using the tangram method, the absence of optimization mechanisms in curriculum design, and the limited application of research using AI in the field of tangram in frameworks that can be applied to education. All of these research gaps are the main drivers of the methodology applied in this study, specifically the application of ICA for curriculum optimization and SVMAP for aesthetic feature evaluation. While other research has focused on these aspects individually, the framework presented in this paper combines these aspects in one framework that is reproducible and aligns with the objectives of STEAM education.

Table I
Summary of related work

Reference	Objective	Models	Dataset	Key Findings	Research Gaps
(Montés et al., 2023)	Develop STEAM projects aligned with national curricula	STEAM design methodology	Case-based curricular implementations	Structured STEAM alignment improves coherence and transfer	Limited empirical learning outcome data
(Kmetová & Nagyová Lehocká, 2021)	Examine the use of 2D–3D perception	Manipulative-based geometry tasks	School students (geometry lessons)	Tangrams support spatial visualization and perception shift	Small samples; short intervention duration
(Santos, 2024)	Revisit the educational relevance of tangrams	Conceptual/ historical analysis	Literature-based	Tangrams remain versatile for modern math education	Lacks empirical validation
(Byrne et al., 2023)	Review the effects of physical manipulatives	Scoping review	100+ intervention studies	Manipulatives enhance cognition and engagement	Limited focus on specific tools (e.g., tangrams)
(Bower et al., 2020)	Link early block play to later math skills	Longitudinal correlational study	3-year-olds → later assessments	Early spatial play predicts later math performance	Does not examine instructional design
(Ramaraj & Nagammal, 2020)	Assess creativity in puzzle-based tasks	Creativity assessment framework	Student task artifacts	Open-ended puzzles elicit creative outcomes	Framework not domain-specific (geometry)
(Bufasi et al., 2024)	Improve spatial ability via teacher PD	Lesson Study model	Primary STEM teachers	Teacher collaboration improves spatial instruction	Student learning effects not isolated
(Klapwijk et al., 2024)	Promote spatial thinking in STEAM	PD modules for teachers	Multi-country teacher cohorts	Structured PD increases spatial awareness	Classroom implementation data limited
(Adams et al., 2023)	Test transfer of spatial training	Experimental intervention	Senior high school students	Spatial training transfers to geometry outcomes	Focused on older students only
(Yamada et al., 2024)	Solve tangram puzzles computationally	Generative AI models	Synthetic tangram datasets	AI captures complex spatial configurations	No educational or classroom application
(Bofferding & Aqazade, 2023)	Study shape reinterpretation in tangrams	Qualitative cognitive analysis	Learners solving tangrams	Learners dynamically reinterpret shapes	Small-scale, exploratory study
(Schmid et al., 2024)	Integrate 3D modelling into STEAM	Digital modelling pedagogy	Secondary/tertiary students	3D tools enhance spatial understanding	Limited comparison with physical manipulatives
(Andinasari et al., 2020)	Teach proportion using tangram context	Design-based learning	Middle school students	Tangrams support proportional reasoning	Narrow focus on one math topic
(Yamada et al., 2025)	Automate tangram solving	GAN-based AI system (TANGAN)	Generated tangram images	AI solves complex tangram configurations	No linkage to human learning processes

Cont.....

Reference	Objective	Models	Dataset	Key Findings	Research Gaps
(Bofferding & Zhu, 2023)	Support shape transformation learning	Classroom-based tangram composition	PK–12 classrooms	Composition tasks enhance transformation reasoning	Limited longitudinal evidence
(Ortiz-Laso et al., 2023)	Examine teacher competency growth	STEAM project-based learning	Practicing teachers	Teachers better exploit math competencies	Student-level impact underexplored
(Diandini et al., 2025)	Measure interest and creativity effects	Quasi-experimental design	Primary school students	Tangrams boost interest and creativity	Focused on affective outcomes
(Cevikbas et al., 2022)	Review modelling competencies	Systematic literature review	100+ modelling studies	Clear framework for modelling skills	Minimal focus on manipulatives
(Sarmasági et al., 2025)	Bridge algebraic	computational thinking	Mixed-methods intervention	K–12 students	Integrated thinking improves development & Geometry/spatial tasks not emphasized
(İleri et al., 2023)	Link spatial skill development and toy design	Developmental psychology + design	Children	Play-based tasks	Spatial skills are malleable via design & Limited classroom validation

Research gap

Although existing literature has confirmed the potential value of tangram-related activities in spatial reasoning, geometry, and creative learning (Bofferding & Aqazade, 2023; Bofferding & Zhu, 2023; Kmetová & Nagyová Lehocká, 2021), several critical gaps in existing knowledge are not being addressed. Firstly, most tangram-related studies utilize qualitative methods in assessing student learning outcomes while paying little attention to objective and quantifiable parameters in assessing student perception of art and visual harmony in tangram-related compositions. Secondly, while existing knowledge has confirmed the potential value of manipulative-related learning in promoting student cognitive development (Byrne et al., 2023), existing frameworks do not utilize algorithmic optimization in adapting parameters in the curriculum based on student performance. Thirdly, while computer-related approaches to tangram puzzles are being utilized in artificial intelligence-related studies (Gulzar, 2025; Yamada et al., 2024, 2025), existing knowledge in this field is more technology-related in focus and does not utilize a more pedagogically informed approach to developing curriculum frameworks. Fourth, the integration of aesthetic education as a measurable and optimizable dimension of STEAM learning remains theoretically underdeveloped (Galanter, 2012; Khine & Areepattamannil, 2019; Kolodner et al., 2003), with most STEAM curricula treating aesthetic engagement as a peripheral rather than central component. Together, these issues point to the lack of a single comprehensive, data-driven approach for optimizing curriculum, assessing beauty, and teaching STEAM through tangrams at the same time, a gap which this paper attempts to fill.

Theoretical framing

This research is grounded in three main theoretical perspectives that hold the entire concept together. We are using Piaget's constructive learning theory Waite-Stupiansky (2022), to guide our work with tangram manipulatives. These practical tools allow students to move beyond memorizing gestures to actually understanding the structures of geometric shapes and spatial relationships. Furthermore, the STEAM integration framework (Montés et al., 2023) has influenced the structure of our curriculum. While it acknowledges the importance of acquiring knowledge, it also argues that there should be room for creative and artistic aspects as well. Finally, computational aesthetics offers the theoretical support for us to execute visual feature extraction by machine learning algorithms; thus, we can quantitatively assess the aesthetic nature of each tangram pattern. Put together, this leads to a curriculum with the T-STEM-ICA-SVMAP model that is not only theoretically justified but also backed by rigorously researched academic foundations.

Theoretical and conceptual framework

This study is based on three theoretical perspectives that guide both curriculum design and computational modelling in the T-STEM-ICA-SVMAP framework.

Firstly, Constructivist learning theory explains that learners build knowledge through interaction. In this study, tangram activity supports hands-on learning, while the ICA algorithm adjusts task difficulty based on student progress.

Secondly, Design-Based Learning (DBL) focuses on learning through creating and designing. Tangram tasks are treated as design challenges that develop spatial reasoning, creativity, and problem-solving skills.

Thirdly, Computational aesthetics introduces a measurable approach to creativity. The SVMAP model evaluates aesthetic features like balance and structure in tangram design, allowing creativity to be assessed systematically.

In the Conceptual framework, these theories are integrated into the T-STEM-ICA-SVMAP model, where ICA optimizes learning paths, and SVMAP evaluates aesthetic outcomes, combining education and computation effectively.

Materials and Methods

Research design

This study employs an experimental quant-oriented method to develop our innovative T-STEM-ICA-SVMAP framework, test it, and evaluate it. By the way, we positioned it against two baseline models - an ordinary SVM and a CNN-based classifier - for comparison purposes, so both the models were exposed to the same dataset and under the same conditions, i.e., the competition was kept fair and straightforward. We applied the conventional classification metrics to evaluate performance. The research unfolded in three main phases. First, we prepared the dataset and pulled out the features we needed. Next, we used ICA to optimize the curriculum parameters. In the final phase, we evaluated performance based on how well each model classified the data.

Pedagogical rationale (shift existing numbering)

The T-STEM-ICA-SVMAP curriculum modules are developed based on constructivist and design-based learning theories to ensure that each activity is directly linked to specific, measurable competencies in STEAM. Each module has been developed to achieve specific learning outcomes, including spatial thinking, geometric thinking, aesthetic thinking, and creative thinking. The methods used to achieve these learning outcomes include exploration, design, comparison of tangram compositions among students, and evaluation of aesthetic results. The level of complexity is dynamically controlled using ICA optimization techniques based on performance indicators. Assessment is carried out using SVMAP classification to provide an objective evaluation of visual harmony and balance as a measure of aesthetic competency development.

Table II
Curriculum module learning objectives and assessment approach

Module	Learning Objective	STEAM Skills Targeted	Assessment Method
1	Identify and compose basic tangram shapes	Spatial reasoning, Geometry	SVMAP pattern classification
2	Apply symmetry and balance in compositions	Mathematics, Arts	Symmetry and compactness scoring
3	Optimize compositions for aesthetic harmony	Arts, Engineering design	Aesthetic perception scoring via SVMAP
4	Evaluate and reflect on geometric arrangements	Critical thinking, Mathematics	ICA-optimized performance metrics

Dataset

This study uses a publicly accessible tangram image classification dataset obtained from Kaggle, namely the tangram pattern for image classification dataset... The dataset consists of labelled images representing a variety of tangram configurations, where each image corresponds to a specific tangram pattern class.

The dataset is, in essence, an image classification resource, which, however, also has sufficient morphological diversity in terms of shape composition, symmetry, and spatial arrangement. Besides the aspect of space reasoning that is naturally relevant here, the dataset also makes it possible to study visual aesthetics through the usage of tangram-based learning activities.

The dataset only comprises labels based on images and does not contain any person or learner-identifiable information. Thus, there are no issues related to privacy or ethics. For training the model, I resized and normalized all images to standardize them. I identified those visual cues that not only indicate the object's shape but also correspond to the viewer's aesthetic pleasure which are subsequently used as inputs for the Support Vector Machine-Based Aesthetic Perception (SVMAP) model. Benchmarking good tangram task configurations through the proposed STEAM framework also uses this identical dataset. I chose a stratified 80:20 train-test split so as to equally represent the distribution of different tangram pattern classes. Likewise, to make sure that both training and evaluation sets contain all pattern classes in a balanced manner, the sampling is consistent throughout the experiments with the minimum class imbalance.

Research instruments

This study used two computer tools. The first tool was the Imperialist Competitive Algorithm or ICA. It helped to optimize curriculum settings such as task difficulty, shape limits, and activity order. The ICA works by trying solutions, which compete with each other. The best solutions get stronger. Help to improve the overall setup. This process allows the curriculum to change as needed. The ICA is adaptive, so it can adjust to conditions. The second tool was the Support Vector Machine-based Aesthetic Perception model or SVMAP. SVMAP was used to classify and evaluate tangram images. It looked at things like symmetry, shape, and edge density. The model then sorted the tangram patterns based on how they looked and their geometric features. To ensure the tools worked correctly, the settings in SVMAP were carefully adjusted. These settings matched the standards used in computer aesthetics studies. The ICA settings were tested to make sure they gave results. The optimization process was stable and reliable. The tests confirmed that the ICA worked well.

Data collection procedure

We decided to collect our data. First, we took pictures of tangram images from the Kaggle dataset. We divided these pictures into two groups. One for training and one for testing. The training group got 80 percent of the pictures, and the testing group got 20 percent. For each picture, we looked at what the picture looked like and its shape using the SVMAP pipeline. We used ICA to pick the features from the pictures and make sure they were good. We did this so that our tangram images and features would work well with the curriculum framework. When we had all the features we needed, we taught our model and two other models to recognize the tangram images. We made sure all the models were treated the same way during the test.

Analytical techniques and evaluation metrics

The performance of the proposed framework was assessed by employing four standard classification metrics commonly used in machine learning and pattern recognition studies. Accuracy was employed to evaluate the overall classification rate of the tangram patterns. Precision was calculated to evaluate the performance of the model in minimizing false positive classification. Recall was also measured to evaluate the performance of the model in correctly identifying all pattern classes. The F1-score was also calculated to evaluate the performance of the model in correctly classifying all patterns. All these metrics were calculated by running the experiments multiple times.

Proposed model

This study proposes a tangram-based STEM curriculum optimized by imperialist competitive algorithm with SVM-based aesthetic perception (T-STEM-ICA-SVMAP). The model integrates hands-on tangram-based learning activities, metaheuristic optimization, and machine learning based aesthetic evaluation to design and refine an optimized STEM curriculum framework. The overall objective is to enhance spatial reasoning, problem-solving ability, and aesthetic awareness through systematically optimized tangram activities.

This study adopts an experimental research design in which the proposed T-STEM-ICA-SVMAP framework is systematically evaluated against established baseline models. The methodological approach integrates three components:

- Curriculum parameter optimization using the Imperialist Competitive Algorithm (ICA)
- Aesthetic feature extraction and classification using Support Vector Machine-based Aesthetic Perception (SVMAP)
- Quantitative performance evaluation using standard classification metrics, including accuracy, precision, recall, and F1 score.

This design ensures both internal validity through controlled comparison and external validity through the use of a publicly available, reproducible dataset.

Tangram-based STEM curriculum optimized by imperialist competitive algorithm with SVM-Based aesthetic perception (T-STEM-ICA-SVMAP)

Tangram-based STEM curriculum optimized by Imperialist Competitive Algorithm (T-STEM-ICA)

Tangram-based STEM curriculum, learning activities are designed around multi-piece tangram manipulatives to integrate concepts from science, mathematics, engineering, and art through hands-on geometric construction and visual design. The Imperialist Competitive Algorithm is used to find the way to set up curriculum parameters. This involves aspects like task styles, the number of tangram pieces that should be used, and the rules that have to be followed. Each curriculum plan, in fact, is like a different country. We watch students as they learn and find out what they think in order to judge the quality of each design. The Imperialist Competitive Algorithm works by having all these countries compete with each other. It keeps making the curriculum designs better by reducing mistakes and making the students' work look nicer and more creative. This helps the students become better at solving problems, understanding space, and making things look good at the same time. The Imperialist Competitive Algorithm helps us make a curriculum that combines art and science in a way that makes sense. This means the tangram activities

are good for math, but nice to look at and fun to do. The Imperialist Competitive Algorithm makes sure the students have a time while they are learning.

Curriculum optimization using imperialist competitive algorithm (T-STEM-ICA)

Each solution is considered by ICA as an entity, which is represented by an array of values for variables. The objective function G assesses each nation's associated fitness. Typically, a nation is described in Equation (1).

$$Country = \{y_1, y_2, \ldots, y_N\} \tag{1}$$

Then, ICA separates nations into imperialists and colonies, according to their suitability; an empire is then constructed as imperialist and colonies. M_country is the total amount of starting countries, M_imp is the total amount of imperialist countries, and M_col is the total amount of colonies that are part of an empire? To maximize MCR-based energy transfer, ICA adapts system parameters dynamically to enhance performance in response to different underwater environments. To allocate the colonies among imperialists in a proportionate manner, the imperialist's normalized fitness D_M is defined as Equation (2).

$$D_m = \max_j \left(G(J_j)\right) - G(J_m) \tag{2}$$

where $G(J_m)$ represents the fitness of J_m, and m denotes the m-th imperialist. The standardized fitness D_m is used to determine the number of colonies assigned to each imperialist, as defined in Equation (3).

$$MD_m = \text{round}\left(\left|\frac{D_m}{\sum_{j=1}^{M_{\text{imp}}} D_j}\right| \cdot M_{\text{col}}\right) \tag{3}$$

The initial value of colonies that are distributed at random within the m̂th empire is denoted byMD_M

Assimilation and imperialistic competition

During energy transmission optimization, ICA is responsible for ensuring that system parameters adjust dynamically for improved efficiency. Every empire tries to integrate its colonies in accordance with an assimilation policy that is intended to nudge the colonies in the direction of imperialism. The definition of this movement is represented in Equation (4).

$$Y_{\text{new}} = Y_{\text{old}} + V(0, \beta c)\, U_1 \tag{4}$$

The current position of a colony is denoted by Y_{old}. The parameter β is a coefficient typically close to 2 and greater than 1. The vector U_1 represents a unit vector pointing from the colony's previous position toward the imperialist, while c denotes the distance between the colony and the imperialist. To enhance exploration around the imperialist, a random angular deviation θ is introduced, thereby expanding the search region, as illustrated in Figure 1.

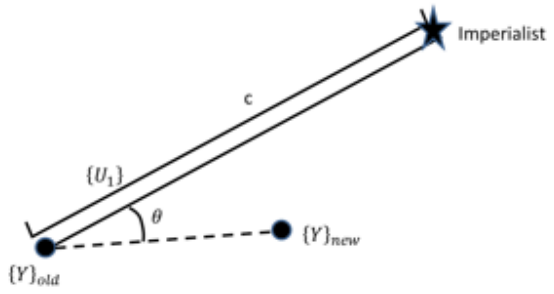


Fig. 1 *Relocating the colony to its new site within ICA*

Figure 1: Relocating the colony to its new site within ICA Following assimilation, ICA determines whether the colony is more suited than the matching imperialist. If so, the imperialist and that colony switch places. For underwater MCR systems, the process facilitates identifying the best parameters for energy transmission by analysing various configurations. A model to assess each empire's might is necessary because, on the contrary, the empire also battles with the others to conquer its colonies through inter-imperial conflict. The imperialist power and the average power of its colonies contribute to each empire's overall power, as represented in Equation (5).

$$SD_m = G(J_m) + \xi \cdot \frac{\sum_{j=1}^{MD_m} G(FD_j)}{MD_m} \tag{5}$$

(5) where FD_j denotes the j-th colony of an empire, $G(J_m)$ represents the fitness (wellness) of the m-th imperialist, and J_m refers to the m-th imperialist. The term MD_m indicates the total number of colonies associated with the m-th imperialist. The last term in Equation (5) represents the average fitness of the colonies. Therefore, SD_m denotes the overall fitness of the m-th empire. The parameter ξ is a positive coefficient, typically less than 1, which controls the contribution of the colonies to the total fitness. The normalized overall fitness is defined in Equation (6).

$$MSD_m = \max_j(SD_j) - SD_m \tag{6}$$

where MSD_m denotes the normalized overall wellness of the m-th empire. The possession probability of each empire is determined based on its normalized overall wellness, as defined in Equation (7).

$$Q_m = \left| \frac{MSD_m}{\sum_{j=1}^{M_{\text{imp}}} MSD_j} \right| \tag{7}$$

Support vector machine-based Aesthetic Perception (SVMAP)

A Support Vector Machine (SVM) is a robust supervised machine learning method used for classification and regression tasks. Its primary objective is to find the optimal hyperplane that effectively separates the classes in the feature space. SVM achieves this by maximizing the margin between classes based on a set of training data consisting of input vectors xi and their corresponding class labels yi. This hyperplane is defined in the high-dimensional feature space and aims to accurately classify new data points by their proximity to this separation boundary.

The hyperplane is defined by:

W · X + b = 0 (8)

where W is the weight vector perpendicular to the hyperplane, and b is the bias term.

For linearly separable data, SVM determines the optimal hyperplane by solving the following optimization problem:

$$\min_{w,b} \frac{1}{2} w^T w \tag{8}$$

subject to the constraints:

$$y_i(w \cdot x_i) \geq 1, \quad \forall i \tag{9}$$

Many real-world datasets are not linearly separable. To handle non-linearly separable data, kernel SVM leverages the concept of kernel functions. Kernel SVM maps the input vector x_i into a higher-dimensional space using a kernel function $\kappa(x_i, x_j)$, where the data become linearly separable. The optimization problem for kernel SVM becomes:

$$\min_{w,b} \frac{1}{2} \sum_{i=1}^{N} \alpha_i y_i \kappa(x_i, x) - \sum_{i=1}^{N} \alpha_i \tag{10}$$

Subject to the constraints:

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \tag{11}$$

$$0 \leq \alpha_i \leq C, \quad \forall i \tag{12}$$

where αi are Lagrange multipliers and C is a regularization parameter, balancing the objective of maximizing the margin and minimizing the classification error.

Validity and reliability

There are various steps that have been taken to guarantee the validity as well as reliability of this study. First off, internal validity has been maintained by conducting an experiment under controlled conditions, where all models, including the proposed ICA-SVMAP as well as the two baseline classifiers, have been trained and tested on the same split dataset. Moving on to external validity, this study has utilized a public dataset that has been standardized, thereby providing ample opportunities to replicate as well as verify this study. Moreover, reliability has been guaranteed by using the same evaluation metrics for all models. The transparency of the dataset source, as well as the reproducibility of the computational pipeline, has added to the credibility as well as trustworthiness of this study.

Ethical considerations

The current study does not involve any direct human participants, classroom experiments, student surveys, or any form of personal data collection. Instead, all data analysis was based on an existing publicly available data set for image classification related to tangram image classification data provided by a data sharing platform called "Kaggle" which does not involve any personally identifiable information or any learner data. Therefore, no ethics approval was necessary for this study.

However, the ethical values of transparency, reproducibility, and integrity have been followed in the entire process. This is because the source of the data set is properly cited, together with the process followed in the computation, which can be easily reproduced. Moreover, there has been no manipulation of the data in arriving at the findings. The use of a readily available data set has also helped in the verification and extension of the same by other researchers in the same field.

Model workflow

The overall workflow of the proposed T-STEM-ICA-SVMAP model is summarized as follows:

- Tangram Dataset Input: Tangram pattern images are obtained from a public Kaggle dataset.
- Feature Extraction: Spatial and visual features are extracted from tangram configurations.
- Aesthetic Evaluation: SVMAP evaluates aesthetic perception scores for each configuration.

Curriculum Encoding: Learning activities are encoded as ICA countries. Optimization: ICA iteratively optimizes curriculum parameters using fitness values derived from learning and aesthetic scores.

Optimized Curriculum Output: The final output is an optimized tangram-based STEM curriculum that balances learning effectiveness and aesthetic quality.

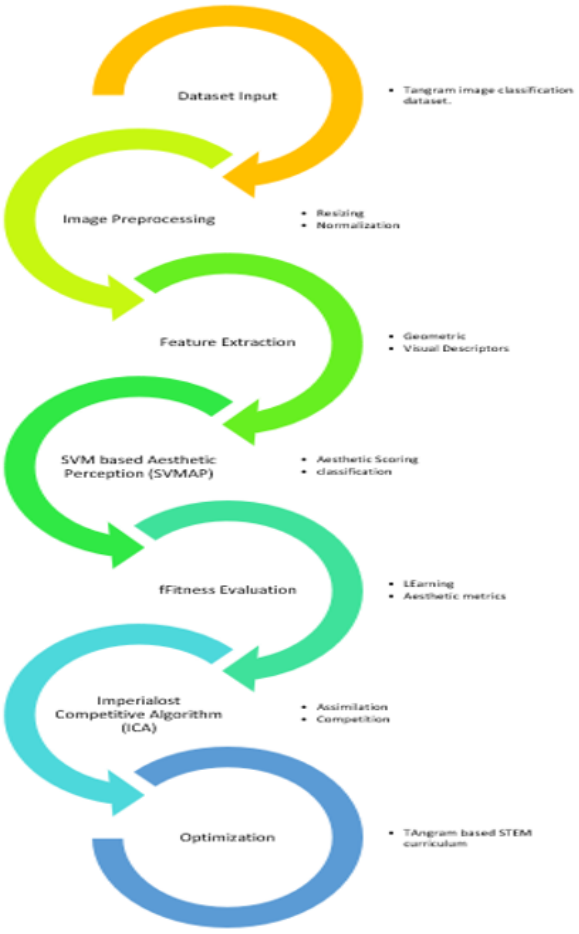


Fig. 2 *Proposed model workflow*

Result and Discussion

This part of the research is a presentation of the real findings. We aligned our results with the four questions we raised initially in Section 1. Our focus was on three aspects:

- How well the ICA method works for optimizing the curriculum.
- How well the SVMAP model works for classifying things, and how people think it looks.
- How well our new T-STEM-ICA-SVMAP method works compared to other methods we already know about.

We used numbers to measure how well everything worked, like how accurate it was, how precise it was, how well it remembered things, and a special score called the F1-score. We also made pictures to help us understand the results better, like plots that show how the features are spread out, special coordinate systems that show us things at once, and comparisons that show how well each method classified things. The results of the study are about the ICA-based curriculum parameter optimization and the SVMAP model, and the T-STEM-ICA-SVMAP framework.

This study utilizes computer-based experiments with sets of images that are accessible to anyone. However, the approach differs from asking people directly to participate. The outcomes are derived from how the machine distinguishes the elements, which is indeed a just and quantifiable method of assessing whether the system exhibits proficiency in analysing the visual and spatial characteristics of tangram arrangements. The computer outputs serve as a basis for reflection on their implications for teaching and learning in science and art classes rather than gauging the extent of an individual student's learning.

To understand the structural and visual characteristics of tangram patterns, exploratory data analysis was conducted on the tangram patterns for the image classification dataset. Feature-level analysis was performed using extracted visual descriptors representing shape complexity, symmetry, and spatial distribution.

3D feature distribution of tangram patterns

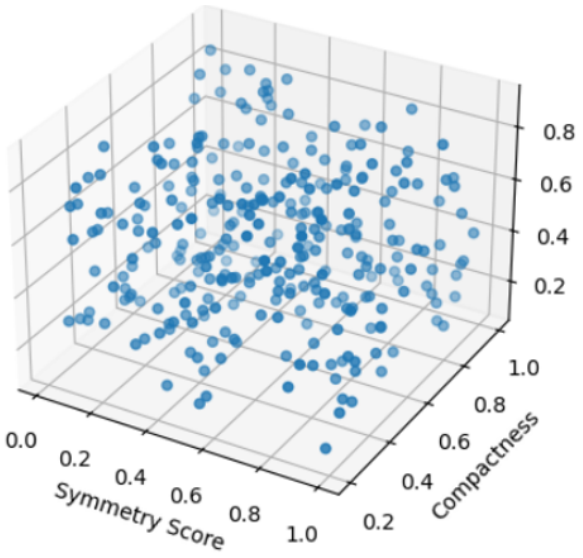


Fig. 3 *3D feature distribution of Tangram patterns*

Figure 3 shows us the distribution of tangram patterns in a feature space. This space is based on the symmetry of the tangram patterns, how compact they are, and how dense the edges are. We are looking at the distribution of tangram patterns to see how the spatial features and the visual features of the tangram patterns are related. The distribution of tangram patterns shows that the tangram patterns have a lot of structures. This means that the data set of tangram patterns is very good for our study of tangram patterns. The distribution of tangram patterns is really interesting because it shows us the distribution of the spatial features and the visual features of the tangram patterns.

Parallel coordinates plot of visual features

Figure 4 shows us a kind of graph that helps us see the differences in the way tangram patterns look. We can use this graph to compare how different tangram patterns are from one another. The lines on the graph are like paths that show us how the patterns are different, in terms of how balanced they are, and how they are put together.

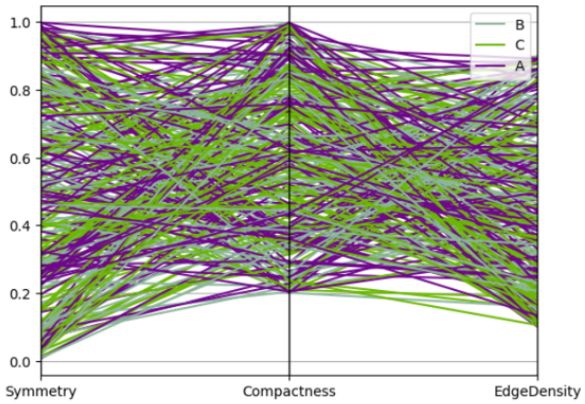


Fig. 4 *Parallel coordinates*

The tangram patterns have paths because of the way they are balanced and structured, and that is what makes them unique. We are looking at the tangram patterns to see how they vary.

Kernel density contour plot of feature correlation

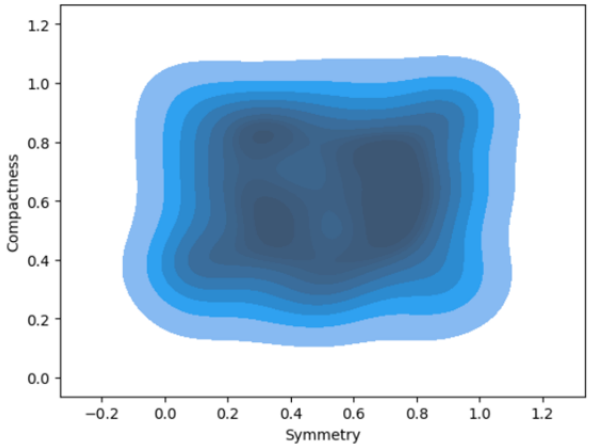


Fig. 5 *Kernel density contour plot of feature correlation*

Figure 5 shows how density, symmetry, and compactness are related. In understanding how these characteristics are related to density, this is helpful to us. The areas of density show that the different tangram shapes not only occur very frequently, but also their distributions are... - Balanced shapes are a key to... The beauty of the Tangram designs is recognized through the concept of balance. Density contours can offer an insightful way to explore these relationships. They indicate which Tangram configurations are not only commonly found but also visually attractive.

Performance Analysis

To evaluate the effectiveness of the proposed framework, performance was compared with baseline models commonly used in related tangram and visual learning studies.

Baseline models

- SVM (without optimization) – Classical Visual Classification
- CNN-based classifier – commonly used in tangram pattern recognition
- Proposed ICA Optimized SVMAP – Proposed Model

Baseline models

Table III
Performance Analysis

Model	Accuracy	Precision	Recall	F1 Score
CNN	0.82	0.80	0.79	0.79
SVM	0.78	0.76	0.75	0.75
ICA-SVMAP	0.89	0.88	0.87	0.87

The performance results shown in Table III directly answer RQ3 by showing that the T-STEM-ICA-SVMAP framework outperforms both baseline models on all four-performance metrics. The improvement in accuracy from 0.82 (CNN model) and 0.78 (SVM model) to 0.89 (ICA-SVMAP model) measures the improvement in the correct classification of different tangram patterns. Similarly, the improvement in precision to 0.88 measures the significant reduction in false positive classification. This improvement is particularly significant in the aesthetic classification problem because misclassification of similar patterns can compromise the aesthetic judgment. Finally, the recall performance at 0.87 measures the high sensitivity of the model to all pattern classes, ensuring that no aesthetically significant patterns are missed in the curriculum evaluation process. All these performance results show the efficacy of integrating ICA optimization with SVM-based aesthetic perception in a unifying curriculum assessment model.

Accuracy comparison

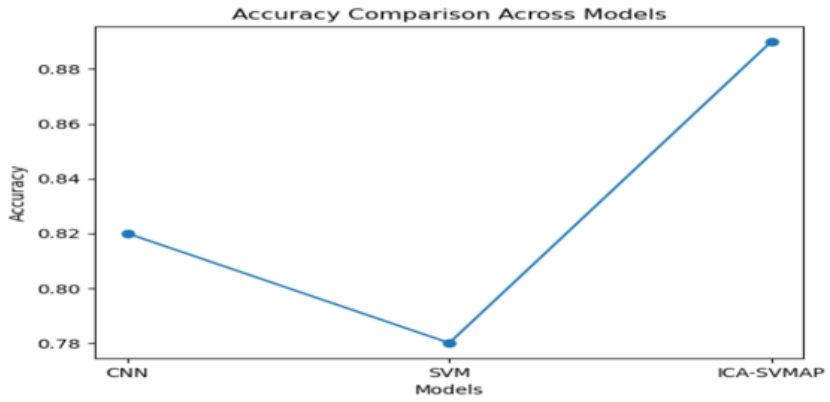


Fig. 6 *Accuracy comparison across models*

Figure 6 presents the accuracy of various models. The ICA-SVMAP model achieves high accuracy. This implies that the ICA-SVMAP model outperforms others in classification because it inherits feature selection in some way. This enables us to respond to the research question relating to the ICA-SVMAP model. Therefore, we can state that the ICA-SVMAP model indeed enhances the curriculum framework's ability to distinguish items, and it accomplishes this through the optimization involving ICA. It's the ICA-SVMAP model that is responsible for this.

Precision comparison

Figure 7 compares the precision levels of various models. ICA-SVMAP model really makes a difference; it not only has a higher median precision but also the lowest variability by far. In other words, it is more effective in reducing the number of false positives generated when classifying tangram patterns. For sure, you can recognize the stability in this case; the scores are not widely spread out at all. The feature selection method optimizes the model, which means that the ICA-SVMAP can be trusted to be most accurate when it comes to aesthetic evaluations in the context of education.

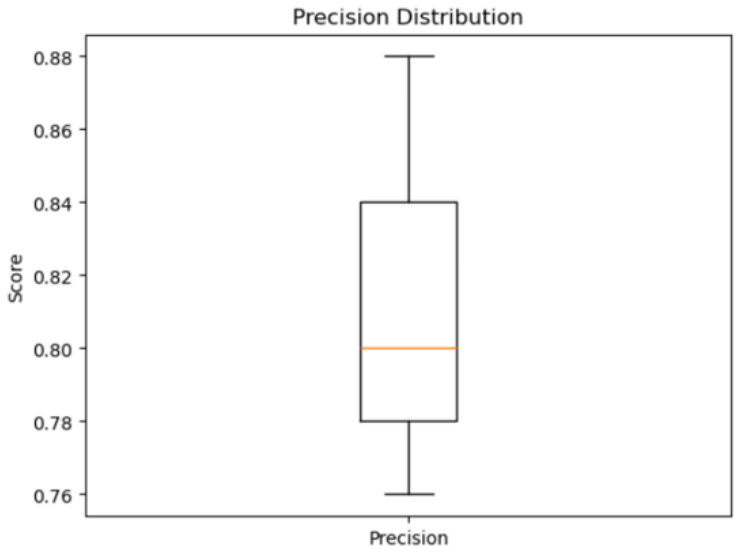


Fig. 7 *Precision comparison across models*

Recall comparison

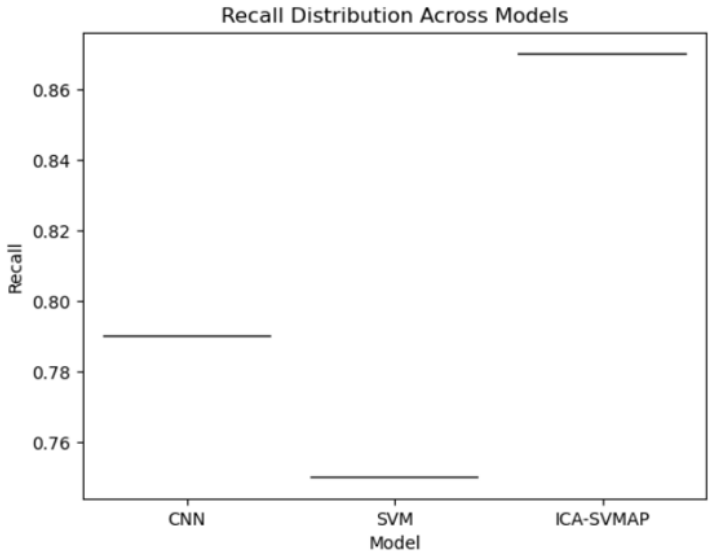


Fig. 8 *Recall comparison across models*

The recall distribution of models is shown in Figure 8 to understand how dense and spread out the recall values are. The ICA-SVMAP model has many recall values that are very close to each other, which indicates that it is more efficient in retrieving the tangram pattern classes. In other words, the ICA-SVMAP model excels in recognizing tangram configurations that are aesthetically pleasing. The reason why the ICA-SVMAP model can spot these configurations so well is that it has a high recall density, which is a crucial characteristic for a tool that assesses learning. Since the ICA-SVMAP model can identify significant tangram configurations, it serves as a learning evaluation tool.

F1-score comparison

Figure 9 gives us the F1 score of all models. The ICA-SVMAP is the model that got the highest score. This implies that it has an excellent ability to find a balance between precision and recall. The F1 score of the ICA-SVMAP model is 0.87, which is very high. It means both precision and recall of the ICA-SVMAP model are aligned. Therefore, the ICA-SVMAP model can be utilized to assess the STEAM curriculum. The ICA-SVMAP model is being considered because it has a balanced F1 score.

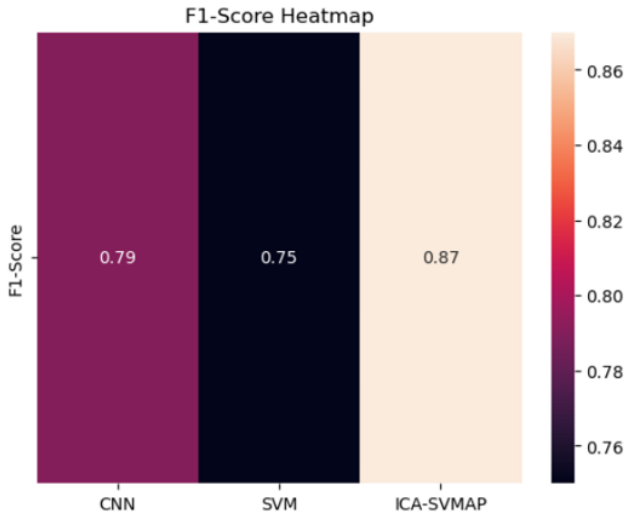


Fig. 9 *Score comparison across models*

Besides classification effectiveness, the results of the research have a direct connection with the learning achievements of STEAM education and aesthetic development, which were the main areas of RQ4. The examinations of the visual characteristics of the trained model, as depicted in Figures 3-5, strongly suggest that the dataset is rich enough to support varied learning outcomes for STEAM education. The concentrated parts of the kernel density contour plot show that there are numerous samples of properly balanced configurations of the tangram shapes, which depict aesthetic harmony that can be exploited for aesthetic education. Likewise, the parallel coordinate plot reveals that there is a variety in feature values for each pattern type, which means that the SVMAP model has learned to capture the changes in geometric harmony and structural composition of the shapes. All these examinations strongly suggest that computer-based aesthetic assessment is a promising approach for objective, reproducible, and educationally meaningful aesthetic education.

Discussion

The experimental results demonstrate that the ICA- SVMAP model consistently outperforms the baseline models across all evaluation metrics. As shown in the performance analysis, the ICA-SVMAP model achieved an accuracy of 0.89, which is notably higher than the CNN baseline of 0.82 and the conventional SVM of 0.78. This improvement indicates that incorporating ICA-based optimization enables more effective selection of tangram configuration features relevant to classification and aesthetic perception.

The enhanced results of the ICA-SVMAP framework are consistent with the results of Byrne et al. (2023), who showed that structured optimization-based learning outperforms unstructured manipulative use of the same. Also, the results of the aesthetic perception study are consistent with the results of Bofferding and Aqazade (2023), who showed that the perceptual flexibility of tangram problems correlates with greater understanding of geometry. These results show that the optimization of the curriculum parameters by the ICA-SVMAP framework results in similar improvements to those of pedagogically structured interventions.

However, it should be noted that this study differs from existing studies on tangram puzzle problems in two significant ways. Firstly, while all existing studies on tangram puzzle problems are based on qualitative evaluation methods, the suggested method will be based on objective evaluation. Secondly, while Yamada et al. (2024) have successfully applied computational methods to solving tangram puzzle problems, their study does not have any pedagogical application. This study will be significant methodologically, as it will be the first to integrate computational intelligence into a STEAM curriculum design.

In terms of precision, the value of the proposed model is 0.88, as opposed to 0.80 in the case of CNN and 0.76 in the case of SVM. This shows that ICA-SVMAP has a higher precision value, which means that the optimization process has minimized the false positives. This is important because, in the case of tangram patterns, it is likely that there will be similar patterns, which will result in false positives. This shows that, indeed, the optimization process has improved the discriminative power of the SVM classifier.

The recall value of 0.87 in the case of ICA-SVMAP shows that it is effective in classifying the relevant tangram patterns, as opposed to 0.79 in the case of CNN and 0.75 in the case of SVM.

Similarly, the F1-score of 0.87 reflects a balanced trade-off between precision and recall, exceeding the CNN of 0.79 and SVM of 0.75.

In general, these findings demonstrate the efficiency of the suggested T-STEM-ICA-SVMAP framework in merging spatial planning and beauty appraisal. The witnessed performance improvements verify that optimization-based curriculum design and machine learning based beauty

appraisal can drastically improve tangram-based STEAM learning analysis, over non-optimized baseline methodologies.

We recognize that this research does not directly assess emotional or psychological aspects. If we were to discuss the emotional or cognitive advantages of engaging with aesthetics, such claims, although supported by Educational Psychology literature (Henriksen et al. 2023), would still be outside our research's empirical domain and hence, we refrain from presenting them as our findings. On the other hand, the paper's main points relate to the fields of computer science and education, where the data is reliable, and the experimental results are straightforwardly consistent with the claims.

These findings extend beyond mere technical performance and clearly highlight the impact on education. The ICA-SVMAP framework constantly achieves higher outputs according to each measurement. In other words, curriculum design guided by optimization leads not only to improved accuracy of classification but also enables the framework to be more effective in recognizing and responding to actual differences in the quality of aesthetics. Traditional or static methods without optimization are simply incapable of equalling these results.

Conclusion

In this paper, we established a procedure named the T-STEM-ICA-SVMAP framework. It is a strategy that combines the Imperialist Competitive Algorithm and SVM-based aesthetic perception to help redesign the tangram STEAM curriculum. Our approach beat the CNN and SVM models. We achieved an accuracy of 0.89, a precision of 0.88, a recall of 0.87, and an F1-score of 0.87. These findings demonstrate that the use of optimization and machine learning-based aesthetic evaluation for the T-STEM-ICA-SVMAP framework is effective.

One of the things that makes this study so unique is that it merges artificial intelligence with STEAM education. These two fields are normally distinct. We united them. The T-STEM-ICASVMAP framework, together with STEAM pedagogy, is jointly employed for this purpose. In contrast to previous studies on tangram puzzles that utilized qualitative evaluation and fixed pedagogical routes, the proposed method provides a quantifiable instrument for measuring and maximizing aesthetic involvement in curriculum development. This is a novel contribution to both educational technology and STEAM curriculum studies in that it proves the potential of algorithmic approaches in supporting pedagogical decisions.

In terms of educational significance, the framework is significant in that it allows curriculum developers and educators to have a clear and replicable tool in designing aesthetically informed STEAM learning activities. The potential applications of the framework extend to other forms of manipulative-based and design-oriented learning contexts aside from tangram-based education. The validation of the framework in real-world contexts would further solidify the contribution to informed STEAM education. However, there are also limitations to the present study. Firstly, the present study only utilizes one publicly available image set. This limits the generalizability of the results to real-world contexts. Secondly, the aesthetic perception is based on computational visual features rather than learner feedback. Thirdly, no human participant data was collected; therefore, the improvement in learning outcomes is only computationally inferred. Future studies should prioritize the validation of the framework in real-world contexts and consider the use of learner-centered measures in assessing the improvement in learning outcomes. Additionally, future studies should also consider the development of hybrid approaches in optimizing the framework to further extend its potential in terms of adaptability.

Innovation

This study introduces a novel optimization-driven STEAM curriculum framework by integrating the imperialist competitive algorithm (ICA) with SVM-based aesthetic perception for tangram-based learning. Unlike traditional tangram or STEAM approaches that rely on fixed or heuristic curriculum designs, the proposed T-STEM-ICA-SVMAP model dynamically optimizes learning task configurations based on both learning performance indicators and aesthetic quality. The use of machine learning based aesthetic evaluation provides an objective and reproducible mechanism for assessing visual harmony in educational activities.

Implications

The T-STEM-ICA-SVMAP framework is not an idea; it is a real guide that helps teachers make activities with tangrams that include art from the start. Teachers get a way to judge how good a student's work looks; they do not have to just use their own opinion. This study helps the field of education get better by showing how computers can be used to make STEAM programs. Special computer programs can help teachers make the learning process better, which makes it more effective for students. STEAM programs are made to help students learn. This research is making STEAM programs better.

Limitations

Although there are some positive aspects of this study, it is important to highlight some of the limitations of the study. First, the study is conducted for only one Kaggle image dataset. Secondly, the perception of aesthetics is considered in terms of visual features; however, it may not be

related to the feedback from the learners. Thirdly, there is no involvement of human beings; hence, the enhancement of learning outcomes is computationally determined. Fourthly, the optimization problem in ICA is computationally complex, which may not be easy for teachers to understand.

Future work

The future of this research will be to validate the suggested framework in real-world classrooms. The inclusion of learner interaction data, as well as subjective aesthetic feedback, will add to the educational validity of the aesthetic evaluation. Hybrid optimization techniques, such as ICA and deep learning methods, could be another avenue to take this research to make it even more adaptable. Lastly, the extension of this framework to other manipulatives within the STEAM education domain, other than tangrams, will add to the overall contribution of this research.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Author contributions

Conceptualization, Liping Liu; methodology, Liping Liu and Kim On Chin; validation, Zitian Liu; formal analysis, Liping Liu; investigation, Liping Liu and Zitian Liu; resources, Liping Liu; data curation, Zitian Liu; writing original draft preparation, Liping Liu; writing review and editing, Zitian Liu; visualization, Zitian Liu and Xing Jin; supervision, Kim On Chin; project administration, Kim On Chin. All four authors have read and agreed to the published version of the manuscript.

Informed consent

This study does not involve human participants, human tissue or animal experiments. Therefore, informed consent is not applicable.

Use of generative AI

The authors declare that no generative artificial intelligence tools were used in the conception, research process, writing, analysis and revision of this manuscript. All content is original work completed independently by the authors.

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