Shape Recognition in AI Systems – Proposal for Application of the Geometric Ratio Model (GRM)

A π-Free, Ratio-Based Framework for Digital Shape Analysis

Author:

M.C.M. van Kroonenburgh, MSc

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Heerlen, The Netherlands

Abstract

In a world increasingly reliant on digital imaging and artificial intelligence, precise and efficient shape recognition plays a crucial role. Whether it pertains to medical image analysis, 3D modeling, or object detection in satellite imagery—accurately identifying circular or spherical structures remains a persistent challenge. Traditional methods rely on π-based calculations to analyze shapes within square or cubic grids. However, this approach often results in complexity, rounding errors, and inefficiencies, particularly in digital environments where everything is represented in discrete units (pixels, voxels).

The Geometric Ratio Model (GRM), developed by M.C.M. van Kroonenburgh, MSc, offers an alternative perspective: describing shapes based on their relationship to a bounding square or cube without the use of irrational numbers. For instance, an inscribed circle will always exhibit a ratio of 0.7854 (π/4) relative to the perimeter or area of the square in which it resides. This constant enables the recognition of shapes based on fixed ratios, making the process simpler, faster, and more robust within digital systems.

This document presents the GRM model as an innovative, π-free method for geometric analysis, emphasizing applications in AI-driven shape recognition. The use case focuses on detecting circular structures in medical imaging, where the power of ratio-based reasoning leads to more efficient algorithms and improved recognition outcomes. This paper aims to establish the groundwork for broader implementation in digital systems, spanning domains from education to high-performance computing.

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Introduction

In a world where digital systems increasingly make decisions based on visual input, the need for reliable and efficient shape recognition is becoming more urgent. From medical image analysis to automated quality control, from satellite imagery to augmented reality—everywhere, shapes must be detected, classified, and interpreted.

However, modern geometry still heavily relies on the use of irrational constants such as π. This classical approach, while powerful, does not seamlessly align with the functioning of digital systems: in raster structures, based on discrete units, within fixed frameworks. In these contexts, the use of π leads to rounding errors, inefficiencies, and an unnecessarily complex translation between visual shapes and their mathematical representation.

This proposal introduces an alternative that is radically simpler: shape recognition based on ratios within a square or cube. No more π, no derivative parameters such as radius or r^2, but a direct relationship between a shape and the space that contains it. In essence, geometry is reduced to its core: shape as a ratio.

The GRM Model as an Alternative to π-Based Calculations

The Square Perimeter Unit (SPU), Square Area Unit (SAU), and Square Volume Unit (SVU) provide a uniform measurement method for shapes within a square or cube. These three units form the core of the broader Geometric Ratio Model (GRM), which expresses proportions across dimensions using fixed ratios instead of irrational constants. The core of the model is that inscribed shapes always maintain a fixed ratio to their bounding structure:

- An inscribed circle always occupies 78.54% of the perimeter of the square in which it resides (SPU).
- Its area covers 78.54% of the square (SAU).
- An inscribed sphere fills 52.36% of the volume of the encompassing cube (SVU).

These ratios are constant, scale-independent, and perfectly aligned with raster-based digital systems. With this approach, shape recognition is no longer a process of complex estimations but a simple check of ratios—exactly how pixels and voxels already operate.

The GRM model as a new standard for digital shape recognition

In this proposal, the GRM model is concretely applied within the domain of digital shape recognition, with a focus on medical image analysis. Here, recognizing circular or spherical structures—such as tumors, blood vessels, or cysts—is critical for accurate diagnosis.

Using the GRM model, AI algorithms can not only operate faster and more efficiently but also classify more accurately. By employing ratio-based numbers instead of π-dependent estimates, a π-free detection method emerges that better aligns with digital image formats and is less prone to rounding errors or scaling issues.

This case study demonstrates that the GRM model is not only mathematically consistent but also practically applicable and socially relevant.

Problem Statement

Although digital systems are increasingly sophisticated in processing and interpreting image data, the recognition and classification of geometric shapes remain surprisingly complex. The core of this problem does not lie in computational power or algorithms but in the mathematical framework used to describe these shapes.

In many applications—such as medical imaging (MRI, CT scans), remote sensing (satellite imagery), computer vision, and CAD—round or spherical structures are often placed within square or cube-shaped boundaries. Within this digital context, every shape is composed of discrete elements: pixels, voxels, grids. Nevertheless, the underlying computational models are based on analog, continuous mathematics that rely on irrational constants such as π.

This discrepancy results in several practical challenges:

- **Rounding errors**: π cannot be accurately represented in decimal form, which introduces errors in calculations of perimeter and area.
- **Complexity**: Classical formulas necessitate intermediate steps using r, r^2, or volume factors, derived from discrete data.
- **Inconsistency**: Comparing shapes becomes difficult as each calculation is context-dependent and does not occur on a uniform scale.
- **Mismatch with digital structures**: Pixels and voxels operate based on relative positions within a raster, rather than mathematical formulas.

These issues are not merely theoretical. In AI applications, this leads to reduced recognition accuracy, longer processing times, and error-prone classifications. In the medical domain, such shortcomings can directly impact diagnoses. Hence, there is a need for an alternative mathematical perspective that better aligns with the digital reality: scalable, rational, and directly applicable to shapes within square or cube-shaped boundaries.

The GRM model provides precisely this alternative.

Innovative Solution: The GRM Model

Proportion Instead of Calculation Using Constants

The GRM model (Geometric Ratio Model) introduces a fundamentally different approach to analyzing and recognizing geometric shapes. Instead of calculating with irrational constants and derived quantities such as radius or area through π, this model analyzes each shape as a proportion relative to the square or cube in which it is inscribed.

The principle is straightforward: by using the square or cube as a standard reference unit, shapes can be described based on fixed, scale-independent proportions. This approach is consistent, rational, and directly aligns with the digital reality where shapes are nearly always represented within rectangular grids of pixels or voxels.

Key Proportions within the Model

- SPU (Square Perimeter Unit): A perfect inscribed circle has a perimeter that is 78.54% of the perimeter of the square in which it is inscribed.
- SAU (Square Area Unit): The area of an inscribed circle is likewise 78.54% of the area of the square enclosing it.
- SVU (Square Volume Unit): A sphere perfectly fitting inside a cube occupies 52.36% of the volume of the cube.

These proportions derive mathematically from classical formulas but are then simplified into fixed coefficients applicable directly in proportional analysis, eliminating the need for rounding or conversion of irrational numbers.

Benefits of This Approach

- **Dimensional Consistency**: Perimeter, area, and volume are interpreted within a single reference framework.
- **Applicability in Digital Contexts**: Seamless integration with raster-based structures without requiring abstract or continuous geometrical models.
- **Comparability Between Shapes**: By using fixed proportions, shapes can be compared easily and objectively.

The GRM model does not aim to replace traditional geometry but instead provides a complementary framework — an alternative conceptual approach that introduces simplicity and logic in scenarios where traditional geometry is cumbersome, error-prone, or computationally inefficient.

For a detailed derivation of the proportional constants, dimensional consistency, and the theoretical foundation of the model, refer to the accompanying whitepaper: “Geometric Ratio Model: A New Metric for Proportion, Form, and Dimension” (Van

Kroonenburgh, 2025), Available at: www.inratios.com/whitepaper-geometric-ratio-model . This document includes derivations, formulas, applications in 1D–2D–3D, and a mathematical substantiation of the fixed coefficients within the SPU/SAU/SVU framework.

Use Case: Shape Recognition in AI Systems

In many AI applications, accurately identifying geometrical shapes is a crucial step in the analytical pipeline. This is particularly true for medical imaging, where MRI or CT scans are utilized to detect structures such as tumors, blood vessels, or cysts. In this context, shapes are always represented within a grid of pixels or voxels—a digital framework where each structure is enclosed by a square or cube-shaped bounding box.

Current detection algorithms typically base their shape analysis on estimations of edges, radius, and area. To classify a shape as "round," an approximation is made of the radius, and through formulas such as $A = \pi r^2$ or $O = 2\pi r$, the shape is validated. This process requires multiple intermediate steps, is prone to rounding errors, and is often error-sensitive when dealing with imperfect or noisy input data.

SPU/SAU as Accuracy Check

The GRM model offers a direct and scale-independent solution. Instead of deriving the shape itself through complex calculations, it focuses on the proportion between the shape and the space it occupies. For instance, if a structure occupies approximately 78.54% of the area of its enclosing bounding box, it is highly likely to be a circle. This straightforward logic enables shape type verification using a single fixed ratio—without π, without r, and without derivation.

This approach provides three immediate advantages:

- **Speed**: The AI does not need to make separate estimations for \(r\) or \(\pi\). The calculation involves a simple proportional test.
- **Robustness**: The analysis is less sensitive to noise or distortion. Even with imperfect shapes, the ratio remains approximable.
- **Comparability**: Since all shapes are evaluated within the same reference framework, a uniform metric for shape classification emerges.

In practice, this means that the GRM model can be integrated as an additional decision layer in existing classification models or serve as a replacement for current shape recognition logic in scenarios where speed, simplicity, and reproducibility are paramount.

This use case not only demonstrates the applicability of the model but also highlights the added value of proportional thinking in a digital world where everything begins within squares.

Technical Implementation

The implementation of the GRM model within AI systems for image recognition does not require a fundamental revision of existing architectures. Instead, the model serves as an additional lightweight analytical module capable of verifying geometrical shapes based on proportions within their bounding box.

The basic steps for integration are as follows:

- **Detection of bounding boxes**: Utilize an existing object detection algorithm (such as YOLO, Faster R-CNN, or U-Net) to isolate potential structures within rectangular (2D) or cubic (3D) frames.
- **Calculation of the actual area or volume of the object within the box**: This can be achieved through segmentation masks or pixel/voxel counting (e.g., via binarized segmentation).
- **Computation of the relative ratio in comparison to the box**:

$$Ratio = \frac{object's\ area}{box\ 's\ area}\ \ of \frac{object's\ volume}{box's\ volume}$$

Threshold-based evaluation:

Compare the resulting ratio to known fixed SPU/SAU values:

- If the ratio is approximately ~0.785, the structure is likely circular.
- If the ratio is approximately ~0.523, the structure is likely spherical.
- Other values may indicate ellipses, deformations, or irregular structures.

This logic can be implemented as a straightforward, scale-independent rule within an existing pipeline. Furthermore, the ratio can be added as an extra feature to neural network models to enhance classifications or reduce false positives.

Pseudocode Example (2D):

```
#python

box_area = width * height

object_area = np.sum(segmentation_mask == 1)

ratio = object_area / box_area
```

if abs(ratio - 0.7854) < tolerance:

classification = "circle"

else:

classification = "non-circular"

Integration Advantages

- Applicable across platforms (Python, C++, Java, etc.)
- No additional training data is required—the ratios are mathematically derived and universally applicable.
- Independent of scale and resolution, provided the bounding box is accurately determined.

Due to the simplicity of the calculation and the universality of its application, the model is highly suitable for both real-time systems (such as edge devices) and in-depth analysis on server-level infrastructures.

Advantages and Added Value

The GRM model presents an innovative, scalable, and π-free approach to shape recognition within digital systems. The strength of this model lies not only in the simplicity of its foundational ratios but also in its immediate applicability in contexts where speed, reliability, and reproducibility are crucial.

Specifically, the model offers the following advantages:

- **π-free calculations**: By employing fixed proportional numbers instead of irrational constants, geometric analysis is simplified, transparent, and less prone to errors.
- **Simplification of complex calculations**: Traditional approaches require intermediate steps involving radius, area, or volume. The SPU/SAU model relies solely on relative proportions, drastically reducing computational load.
- **Scale independence**: Proportions remain consistent regardless of the absolute size of the object. This makes the model particularly suitable for applications involving varying resolutions and scale levels.
- **Robustness to imperfections**: Even in the presence of deformations or noise, the proportional analysis remains functional as long as deviations fall within a tolerance range. This increases the reliability of classifications in real-world data.

- **Rapid integration into existing systems**: The model can be seamlessly added as an auxiliary analytical tool in existing AI pipelines without requiring retraining of models or infrastructure modifications.
- **Uniform comparison between shapes**: By analyzing each shape within the framework of a square or cube, a standardized metric is established for objective and consistent shape comparisons.
- **Broad applicability**: The model is deployable across diverse domains, including medical imaging, remote sensing, education, architecture, robotics, and industrial image recognition.

Combined, these attributes provide significant added value compared to traditional, π-based methodologies. The SPU/SAU model aligns seamlessly with the digital reality, where geometry is not continuous but discrete, structured, and proportionally constructed.

Overview: Advantages and Limitations in Perspective

Aspect	**Added Value of the GRM Model**	**Limitation**	**Potential Solution**
Mathematical Model	π-free, fixed ratios, simpler computations	Less suited for exact measurements outside the square model	Apply only to shapes within fixed frameworks or combine with traditional geometry when necessary
Scalability	Operates at any scale: pixel to cube	Requires accurate bounding box (otherwise distorted proportions)	Integrate with reliable object detection in advance
Robustness	Better tolerates deformation and imperfection through tolerance thresholds	Less applicable to irregular shapes	Define boundary conditions and employ as an additional classification layer
Digital Integration	Ideal for raster- and voxel-based systems	Less suitable in analog or abstract measurement environments	Retain as a digital analysis tool, not as a universal measuring instrument
Educational Use	Simplifies geometry for students, visually intuitive	Requires a shift in thinking (away from π)	Introduce via instructional materials focusing

Aspect	Added Value of the GRM Model	Limitation	Potential Solution
			on proportional reasoning
Computational Efficiency	Lightweight, suitable for real-time systems	Lacks built-in error correction or statistical margins	Combine with AI confidence scores or neural networks

Recommendations and Next Steps

The GRM model offers a rational, scale-independent, and computationally efficient alternative for shape recognition within digital systems. Its mathematical simplicity and direct applicability make it particularly suitable for environments where speed, repeatability, and consistency are paramount. To further leverage the potential of this model and validate its practical value, the following next steps are recommended:

1. Development of a Proof-of-Concept

Design and implementation of a simple AI pipeline integrating the GRM model as an analytical module. This could be applied within an existing system for medical image analysis, such as supporting the identification of circular structures (e.g., cysts or tumors) through proportional analysis.

2. Validation in Realistic Datasets

Application of the model to existing image data (preferably open medical or industrial datasets) to compare performance metrics such as recognition accuracy, processing speed, and margin of error against traditional approaches. Explicit testing for robustness under noise, distortion, and scale variations should be conducted.

3. Interdisciplinary Collaboration

Seek collaboration with experts in AI, computer vision, medical technology, and didactics to further optimize the model for various domains. Educational institutions could also be involved to evaluate the model's pedagogical value for curriculum integration.

4. Publication and Dissemination

Publish the underlying white paper and proof-of-concept results in relevant scientific journals, conferences, or mathematical innovation platforms. Concurrently, visualizations and explanatory materials for non-mathematical audiences should be developed.

5. Exploration of Additional Applications

Investigate broader areas of application, such as remote sensing, robotics, object classification in autonomous systems, and shape recognition in industrial quality control. Expanding the model to accommodate other basic shapes (e.g., hexagons or ellipses) should also be considered.

By pursuing these steps, a solid foundation can be established for further development, validation, and application of the GRM model in both practical and academic contexts. The model not only provides an alternative to π-based calculations but also introduces a novel perspective on geometry in the digital age.

Sources

The GRM model is an original development by the author, based on classical geometrical principles and derivations of ratios within inscribed shapes in squares and cubes. This proposal does not utilize direct external data or empirical studies but instead draws on relevant literature and conceptual frameworks that align with the foundational ideas of the model.

At present, the model is in its conceptual phase and has not yet been tested or validated within an operational system. This publication serves as a starting point for further implementation, validation, and development.

The following sources and related concepts are key for deeper theoretical understanding and context:

- **van Kroonenburgh, M.C.M. (2025)**. *The Square Perimeter Unit (SPU) Model: A New Metric for Ratio, Shape, and Dimension*.
- **Hartl, M. (2010)**. *The Tau Manifesto*.
  Describes the mathematical and didactic advantages of using the constant τ (tau = 2π) instead of π, advocating simpler formulations in circular geometry.
  Website: www.tauday.com
- **OSF Preprints (2023)**. *A Circle Without Pi*.
  Introduces an alternative approach to the circle via ratios without the use of π.
  Link: https://osf.io/preprints/osf/stwxf
- **Monte Carlo Approaches to Circle Area**.
  Various publications and discussions demonstrate that it is possible to approximate the area of a circle via probabilistic methods (such as Monte Carlo simulations), without direct reliance on π. See relevant discussions on Reddit Math.

These references illustrate the growing international interest in alternative forms of geometric reasoning and π-free approaches. The SPU/SAU model aligns closely with this trend yet distinguishes itself by combining ratio-based thinking with digital grid structures and by offering a consistent system across 1D, 2D, and 3D dimensions.

The objective of this proposal is to open the model for further development and practical application. To this end, the search for a suitable implementation context is ongoing—preferably within fields where shape recognition in digital image data plays a central role, such as medical image analysis, remote sensing, or industrial quality control.