Pixel-Based Ratio Measurement with the GRM Model
A New Digital Metric for Shape Recognition and Calibration

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Abstract
This paper presents the Geometric Ratio Model (GRM)—a digital measurement method that uses pixel counting as the core mechanism for shape recognition and calibration. By calculating the proportion of pixels occupied by a shape within a square or cube, GRM defines fixed ratio standards (e.g., 0.7854 for a circle) that replace traditional π-based geometry. This enables resolution-independent, transparent, and highly efficient classification in rasterized systems. GRM transforms raw pixel data into a reproducible unit of geometric identity, offering practical applications across artificial intelligence, medical imaging, digital education, and design validation. For the theoretical foundation of the GRM system and its dimensional consistency, see:
M.C.M. van Kroonenburgh (2025). The Geometric Ratio Model (GRM): A New Metric for Proportion, Shape, and Dimension. Whitepaper v2.0.

Inhoud

1. Introduction

In today's increasingly visual digital world, systems across industries depend on precise shape interpretation. Whether analyzing medical scans, training AI for object recognition, or developing educational tools for geometry, accurate shape assessment is critical. Yet, most digital platforms rely on classical geometrical principles based on irrational constants like π, which do not align well with the discrete nature of pixel-based imaging.

The Geometric Ratio Model (GRM) offers a groundbreaking alternative. Rather than calculating geometric properties using continuous, analog models, GRM introduces fixed proportional standards—such as 78.54% for circles and 52.36% for spheres—anchored in the geometry of a square or cube. These constants correspond with the pixel or voxel occupancy of perfectly inscribed shapes.

Shape verification and classification through pixel-counting

This new approach lays the foundation for a new digital metric: shape verification and classification through pixel-counting. By comparing the number of pixels a shape occupies within a known bounding square or cube, digital systems can instantly validate its proportional identity—bypassing π, radius, or perimeter approximations altogether.

This document proposes a practical application of this principle. By leveraging the GRM model to create a pixel-ratio-based tool or module, we introduce a fast, intuitive, and mathematically robust framework for shape recognition and digital calibration. This innovation stands to benefit fields from education and diagnostics to CAD systems and artificial intelligence.

2. Problem statement

Modern digital systems rely heavily on shape recognition algorithms to analyze visual data. However, these systems typically use mathematical frameworks rooted in analog geometry—most notably, formulas that depend on π. In practice, this leads to several limitations:

- **Rounding Errors**: Since π is irrational, it must be approximated numerically, causing minor but accumulating inaccuracies—especially in low-resolution or grid-based environments.
- **Complex Computation**: Calculating geometric features like radius, circumference, and area often requires multiple transformation steps, increasing processing time and introducing fragility.

- **Lack of Uniform Metrics**: Different shapes are evaluated using different geometric heuristics, which limits comparability across datasets or systems.
- **Mismatch with Raster Structures**: Digital environments operate on pixels and voxels—discrete units—whereas classical geometry assumes continuous space.

These discrepancies become especially problematic in use cases like medical imaging, where precise identification of circular or spherical structures (e.g., cysts, tumors) is crucial. Without a consistent, pixel-native metric, systems rely on shape estimators that are sensitive to distortion, scale variance, and segmentation noise.

The missing link: A practical metric for digital geometry

The need is clear: a scalable, robust, and computationally efficient method for recognizing and validating shapes that aligns with the discrete nature of digital images. What is missing is a practical, hands-on instrument—an interpretable and programmable metric that directly links pixel occupancy to geometrical identity. The GRM-based pixel ratio method provides exactly that: a simple, fast, and universally applicable metric that transforms digital images into measurable proportional space.

3. GRM as a digital metric

The Geometric Ratio Model (GRM) introduces a fundamental shift in how geometric shapes are interpreted in digital environments. Instead of approximating continuous features like radius, area, or volume, the GRM approach evaluates how much of a square or cube is filled by a shape—as a fixed, proportion-based identity.

This is not merely a simplification; it is a redefinition of measurement within raster structures. Every pixel becomes a unit of evidence. The more closely a shape fills a known percentage of its bounding frame, the more confidently we can identify its geometrical class.

Core ratios in the GRM system

- An inscribed circle consistently occupies ~78.54% of the area or perimeter of its square → defined as 0.7854 SPU/SAU.
- An inscribed sphere consistently occupies ~52.36% of the cube's volume → defined as 0.5236 SVU.

These constants—derived from classical formulas yet simplified for digital application—serve as standard thresholds in a new metric system. Any object whose pixel ratio approximates one of these values can be classified accordingly.

From calculation to verification

Instead of reconstructing geometrical shapes through estimates, the GRM model allows digital systems to verify shape identity through a simple ratio:

$$GRM\ Ratio = \frac{Shape\ Pixels}{Bouding\ Box\ Pixels}$$

This pixel-ratio can be calculated immediately after segmentation, with no further derivation needed. It is scale-independent, unitless, and consistent across dimensions—providing a reliable foundation for digital shape interpretation.

3.1 Interpreting deviations and edge cases

While the GRM model defines exact ratios for ideal geometric shapes—such as 0.7854 for circles and 0.5236 for spheres—real-world data rarely presents perfect forms. In practice, detected shapes may deviate from these canonical values due to irregularities, distortions, or segmentation noise.

Understanding deviations

A ratio of 0.7854 implies a perfect circle inscribed in a square. But what if a measured ratio is 0.72, or 0.67? Such deviations invite deeper interpretation:

- **Slight deviations** (e.g., 0.76–0.78) may indicate a near-circular shape with minor imperfections or noise in the boundary.
- **Moderate deviations** (e.g., 0.65–0.75) could suggest an elliptical form or partial occlusion within the bounding box.
- **Larger deviations** (e.g., <0.60) typically imply irregular, fragmented, or non-circular shapes.

Rather than treating the ratio as binary (match/no match), it can be interpreted as a confidence score, where proximity to canonical GRM values indicates stronger shape identity.

Classification thresholds

To formalize this, a system may define thresholds, for example:

Shape	Expected Ratio	Tolerance Range
Circle (2D)	0.7854	± 0.03 (0.755–0.815)
Sphere (3D)	0.5236	± 0.03 (0.493–0.553)
Hexagon (2D)	0.8660	± 0.03 (0.836–0.896)

These ranges can be refined empirically based on use case, resolution, and application domain. They transform the GRM metric into a classification layer rather than a rigid filter.

Implications for expansion
This principle also enables the GRM model to support additional shapes—such as ellipses, hexagons, or composite structures—by defining their expected pixel ratios within a bounding square or cube. For instance, a regular hexagon inscribed in a square has a fixed area and perimeter ratio of ~0.8660, making it a candidate for GRM-based identification using the same proportional logic.

In this way, the GRM metric evolves from a simple check into a flexible recognition framework, capable of assessing proportional identity under real-world conditions.

4. Pixel ratio implementation architecture

To implement the GRM-based pixel ratio method in practice, a clear modular architecture is essential. This section outlines the recommended processing pipeline—from raw image input to shape classification based on GRM thresholds. The system can be built as a standalone tool, integrated module, or API endpoint depending on the application domain.

4.1 Input and preprocessing

The process begins with a digital raster image in 2D (bitmap, PNG, segmented MRI slice) or 3D (voxel grid, DICOM scan, point cloud). Key preprocessing steps include:

- **Segmentation**: isolate the object of interest (e.g., via thresholding, U-Net, or manual mask).
- **Bounding Box Extraction**: compute the smallest axis-aligned square or cube that fully contains the object.
- **Pixel Count Extraction**:
  - Count the total number of pixels or voxels within the bounding box.
  - Count the number of shape pixels (value = 1) within the same region.

4.2 Ratio computation and comparison

Once both pixel counts are known, compute the ratio:

$$GRM\ Ratio = \frac{Shape\ Pixels}{Bounding\ Box\ Pixels}$$

Then, compare this result to known GRM reference values:

Shape	GRM Ratio	Tolerance
Circle	0.7854	± 0.03
Sphere	0.5236	± 0.03
Hexagon	0.8660	± 0.03

If the ratio falls within the range, the object can be classified as the corresponding shape.

4.3 Output and decision layer

Based on the computed ratio, the system produces:

- **Shape label** (e.g., “circle”, “non-circular”).
- **Confidence score** based on distance from the GRM value.
- **Deviation index** for diagnostic or training purposes.
- **Optional**: classification heatmap or bounding overlay for feedback.

This architecture enables GRM logic to operate as an interpretable decision layer—either standalone or integrated into AI pipelines as a post-processing validator.

4.4 Integration with AI pipelines

The GRM ratio module can function as a standalone verification tool or as part of a larger AI workflow. Common integration points include:

- **Post-segmentation validation**: After neural networks (e.g., U-Net, Mask R-CNN) predict a segmentation mask, the GRM module verifies if the detected shape conforms to expected geometrical proportions.
- **False positive filtering**: In classification or detection models, shapes that do not meet GRM ratio thresholds can be filtered or flagged for manual review.
- **Multi-stage decision systems**: GRM logic can act as a lightweight early-stage classifier or confidence booster for more complex ensemble models.

This modularity makes the GRM method especially useful in edge computing, low-power applications, or environments where explainability is required.

4.5 Performance and scalability considerations

The GRM pixel ratio computation is highly efficient, as it requires only:

- A bounding box calculation (typically O(n) over segmentation mask),
- Two pixel sums (simple binary count operations),
- One ratio calculation and threshold comparison.

This minimal complexity enables the method to run:

- In real time on edge devices (e.g., Raspberry Pi, NVIDIA Jetson),
- As a batch processor over large image datasets,
- Embedded within graphical user interfaces for live feedback in educational or medical tools.

Moreover, since GRM ratios are scale-independent and unitless, they generalize across resolutions and do not require retraining, retracking, or parameter tuning—offering exceptional portability.

5. Added value

The GRM pixel ratio method introduces a number of key advantages compared to traditional shape analysis techniques. Its strength lies in combining mathematical simplicity with digital-native compatibility, offering value in both theoretical and practical contexts.

5.1 π-Free geometry in digital systems

By replacing irrational constants such as π with fixed proportional values (e.g., 0.7854 for circles), GRM enables geometry that is computable, transparent, and error-resistant. This is especially important in environments where floating-point precision or computational resources are limited.

5.2 Universally scalable and unitless

The method operates entirely on relative proportions, not absolute units. As a result, it functions seamlessly across:

- Resolutions (low-res to HD and beyond),
- Scales (from micro-imaging to satellite data),
- Dimensions (2D pixel maps to 3D voxel grids).

This scale-invariance makes the GRM model applicable in almost any digital imaging system.

Important clarification on the radius:
In the GRM model, the perimeter ratio of a circle inscribed in a square is fixed at 0.7854 SPU (Square Perimeter Units). However, this ratio does not define or imply the radius of the circle. A common misconception is that the radius can be derived from the SPU value itself. This is incorrect. The radius is a separate geometric property and is not inferred from the 0.7854 ratio. In a square with a perimeter of 1 SPU (i.e., side length s = 0.25), the radius of a perfectly inscribed circle is exactly 0.1250 SPU, because it equals half the side length of the square, not a fraction of its perimeter. Therefore, any pixel-based system applying GRM principles must treat the radius and the perimeter ratio as distinct, non-interchangeable quantities. Misinterpreting this relationship can lead to geometric inconsistencies or misclassification in shape analysis.

Note*:* The SPU value describes the relative perimeter of the shape within the square. It must not be used to infer length-based values such as radius or diameter.

For a complete derivation of the radius within the GRM framework, refer to the whitepaper: *"The Role of the Radius in the Geometric Ratio Model (GRM)" (2025)*.
This publication formally defines the radius of a perfectly inscribed circle as r = 0.1250 SPU, based on a square with a perimeter of 1 SPU (implying side length s = 0.25). The value is not an estimate, but a fixed, dimensionally consistent quantity derived from the structural logic of GRM-conforming shapes.

Download: The role of the radius in GRM

Deriving the radius from square perimeter (SPU = 1):

In the GRM model, the radius of a perfectly inscribed circle is derived from the known perimeter of the square rather than from the circle's perimeter.

When the square has a perimeter of 1 SPU, each side of the square is:

$$s = \frac{1}{4} = 0.25$$

Since the circle is perfectly inscribed, its diameter equals the side length of the square:

$$d = s = 0.25$$

The radius is therefore:

$$r = \frac{d}{2} = \frac{0.25}{2} = 0.1250$$

This results in the fixed radius value of r = 0.1250 SPU, which is valid across all scales as long as the enclosing square conforms to the GRM definition (perimeter = 1 SPU, with the circle touching all four sides).

This relationship holds regardless of the resolution or unit system and is especially useful in pixel-based systems where each dimension is derived from container logic.

5.3 Low computational load

GRM-based analysis requires only basic operations: pixel counts and a ratio. No trigonometry, square roots, or high-order polynomial fitting is needed. This makes the approach ideal for real-time systems, edge devices, and integration in lightweight applications.

5.4 Robustness to noise and deformation

As long as a shape approximately fills its bounding box according to a known ratio, it can be reliably identified—even in noisy, distorted, or partially segmented data. The fixed thresholds and tolerances allow for fuzzy matching while maintaining classification confidence.

5.5 Educational and didactic strength

The GRM approach promotes geometric reasoning based on visual intuition and ratio logic rather than memorization of formulas. It is ideally suited for use in STEAM education, digital tools for geometry learning, and interactive platforms that emphasize spatial understanding.

5.6 Versatile integration

From AI pipelines to CAD systems and medical imaging tools, the GRM method can be embedded with minimal configuration. Its modularity and independence from external parameters make it easy to adopt across software environments.

5.7 Pixels as direct measurement units

In contrast to traditional geometry, which relies on inferred quantities such as radius or perimeter, the GRM method uses pixel count as a direct, digital-native measurement unit. Every pixel becomes evidence of presence, and every shape is evaluated by how much of the total pixel space it occupies.

This radically simplifies the path from image to interpretation:

- No assumptions about continuity or smoothness are required.
- No conversion between physical and geometric units is needed.

- No dependence on precision floating-point math.

In doing so, GRM aligns with the discrete nature of modern data, where shapes exist not as theoretical curves, but as clusters of counted, quantifiable pixels or voxels. It transforms geometry from formula-driven abstraction into a concrete, countable system.

A practical example: From pixel count to SPU equivalent

In a practical setting, for instance, a detected shape that occupies 7,854 pixels within a bounding square of 10,000 pixels (e.g., 100×100) yields a GRM ratio of 0.7854.
This value matches the SPU (Square Perimeter Unit) standard for an inscribed circle within the GRM framework.
As such, the ratio does not merely serve as a classification threshold—it becomes a direct, reproducible, and resolution-independent measurement unit, functioning as a digital analogue to the SPU (Square Perimeter Unit) in rasterized geometry.

6. Comparison with classical approach

The GRM model offers a fundamentally different perspective compared to classical Euclidean geometry, especially when applied within digital environments. Below is a direct comparison between traditional π-based methods and the GRM pixel-ratio approach, followed by a reflection on what this shift means for digital systems.

Aspect	Classical Geometry	GRM Pixel Ratio Approach
Mathematical Basis	Irrational constants (e.g., π)	Fixed ratios (e.g., 0.7854 for circles)
Input Parameters	Radius, perimeter, area	Pixel count within bounding square/cube
Computational Load	Moderate to high (floating-point math)	Low (counts and ratio comparison)
Error Sensitivity	Cumulative rounding, scale issues	Minimal; pixel-native, robust
Data Structure Fit	Analog/continuous space	Discrete, raster-based systems
Scalability	Resolution- and unit-dependent	Scale-independent, unitless
Interpretability	Abstract calculations	Concrete visual proportions

Aspect	Classical Geometry	GRM Pixel Ratio Approach
Shape Recognition	Indirect (requires reconstruction)	Direct (ratio = identity + confidence)

6.1 Implications of the shift

Switching from classical π-based reasoning to GRM's ratio-based logic transforms the way we interact with geometry in digital environments. Rather than relying on theoretical properties that must be reconstructed or estimated from imperfect data, GRM enables:

- **Direct classification** based on proportion alone;
- **System-neutral measurement** across platforms, resolutions, and domains;
- **New forms of verification** based on relative truth, not absolute formulae.

This redefinition not only simplifies geometric reasoning but also makes it more compatible with modern digital infrastructure, where everything—from images to neural networks—is composed of discrete, countable units.

6.2 Redefining measurement through pixel counting

Perhaps the most fundamental difference lies in how measurement is defined.
In classical geometry, quantities like area or circumference must be inferred from shape approximations, requiring radius estimation and floating-point calculations.
In contrast, GRM operates by directly counting what is actually there—pixels. This makes the method not only more intuitive and explainable, but also perfectly aligned with the structure of digital data.

7. Future directions

The GRM pixel ratio method opens the door to a wide range of future developments, both theoretical and applied. This chapter outlines key areas for exploration, refinement, and integration.

7.1 Expanding the shape catalog

While the GRM model currently defines fixed ratios for circles, spheres, and hexagons, future versions may include:

- Ellipses and ellipsoids (ratio ranges),
- Irregular but symmetrical forms (e.g., rounded rectangles),

- Compound structures (e.g., clusters or repeating units),
- 4D and n-dimensional extensions (VE-n framework).

This expansion requires precise calibration and empirical validation but holds great promise for broader classification capability.

7.2 Tuning tolerances and confidence scoring

Further research is needed to:

- Define robust tolerance ranges for various resolutions and image conditions,
- Integrate ratio deviation as a confidence metric,
- Adapt thresholds dynamically based on system feedback or domain-specific requirements.

Such enhancements will make the method even more resilient and adaptive in real-world applications.

7.3 Open tooling and API integration

To make the GRM method widely usable, the development of open-source tooling is a logical next step. This includes:

- GRM pixel ratio libraries (Python, C++, WebAssembly),
- A command-line validator and GUI prototype,
- API modules for integration into AI pipelines, image processing suites, or educational platforms.

7.4 Real-world use case pilots

The next phase includes piloting the GRM method in:

- Medical image validation tools (e.g., circle- and sphere-like structure detection),
- Digital geometry education software,
- Automated quality control systems in manufacturing (form-fitting and tolerance checks),
- Embedded vision applications (e.g., drones, sensors, wearables).

These pilot cases will demonstrate the model's adaptability, value, and potential societal impact.

7.5 The foundational role of pixel counting

At the heart of all these directions remains a simple yet powerful principle: counting pixels.
It is this shift — from inferred measurements to direct digital evidence — that makes the GRM method scalable, explainable, and ready for integration across disciplines. Whether in medical diagnostics, AI, or design education, pixel-based proportional logic creates a universal foundation for shape understanding in the digital age.

7.6 Practical tolerance logic for GRM-based classification

In real-world applications, perfect geometric forms are rare. Shapes may appear distorted, segmented, rotated, or blurred—especially in low-resolution, compressed, or noisy images. Even small deviations in edge detection or alignment can affect the resulting pixel ratio.

To account for this, the GRM framework supports confidence-based classification using tolerance ranges. Each canonical GRM ratio (e.g., 0.7854 for a circle) can be evaluated not as a strict match, but as a target within a flexible interval.

For example:

- Circle (SPU): 0.7854 ± 0.03 → accepted range: 0.755–0.815
- Hexagon (SAU): 0.8660 ± 0.02 → accepted range: 0.846–0.886
- Triangle (SAU): 0.4330 ± 0.02 → accepted range: 0.413–0.453

These ranges allow the system to tolerate minor geometric inconsistencies while maintaining a high level of classification confidence.

Beyond the number: Structural conformity

Tolerance margins should be used in combination with structural checks to avoid misclassification. A shape may numerically resemble a circle (ratio ≈ 0.785), but if it lacks enclosure symmetry or radial continuity, it may be better interpreted as an ellipse or distorted form.

Key structural criteria include:

- Symmetry: Does the shape exhibit mirror symmetry across its axes?
- Center alignment: Is the shape centered in the bounding square?
- Edge conformity: Does the shape touch or align with the expected edges?

Scoring and threshold strategies

Classification systems can adopt either a binary threshold (match/no match) or a graded scoring model, where confidence is calculated based on:

- Distance from the canonical GRM ratio
- Number and severity of structural mismatches
- Resolution context and segmentation reliability

This transforms GRM classification from a rigid rule set into a resilient, real-world-ready evaluation tool, especially suited for noisy data, AI post-processing, or medical diagnostics.

7.7 Confidence scoring and weighting schemes

While tolerance margins offer a basic way to determine whether a pixel ratio falls within an acceptable range, more nuanced applications benefit from graded confidence scoring. Rather than making binary decisions (match or no match), the GRM framework can assign a confidence level to each shape detection, depending on how closely it approximates a canonical GRM ratio.

This enables systems to:

- Prioritize high-confidence detections,
- Filter ambiguous cases for review or fallback,
- Train models to weigh geometric likelihoods adaptively.

Scoring based on ratio deviation

A basic confidence score C can be computed as:

$$C = 1 \frac{|r_{measured} - r_{GRM}|}{t}$$

where:

- $r_{measured}$ is the observed pixel ratio,
- r_{GRM} is the canonical GRM ratio for the expected shape,
- t is the tolerance range (e.g., ±0.03), and
- C is clamped between 0 (outside tolerance) and 1 (exact match).

For example, a shape with a measured ratio of 0.772 compared to the GRM circle ratio (0.7854), within a ±0.03 tolerance, yields:

$$C = 1 - \frac{|0.772 - 0.7854|}{0.03} \approx 0.55$$

This score can be interpreted or thresholded based on application needs (e.g., accept ≥ 0.8, review 0.6–0.8, reject < 0.6).

Weighted structural scoring

Ratio closeness is only part of the story. A full GRM-conformity score can also include structural weights, such as:

- Symmetry alignment (vertical, horizontal): +0.2
- Bounding box centering: +0.1
- Edge conformity (touching all 4 sides): +0.2

These can be added to or multiplied with the base ratio score to produce a composite confidence index.

Example composite score:

- Ratio score: 0.80
- Symmetry: +0.2
- Center alignment: +0.1
- Edge conformity: +0.2
  → Total score = 0.80 + 0.5 = **1.3** (normalized to scale or used comparatively)

Practical Use

Confidence scoring enables:

- Soft classification in AI/ML pipelines,
- Prioritization in human-in-the-loop systems,
- Statistical aggregation over large datasets,
- Explainability for users and auditors.

In this way, the GRM becomes not just a metric, but a probabilistic decision system, ready for integration in modern shape analysis and interpretation.

8. Limitations and considerations

While the GRM pixel ratio model offers clear advantages in terms of simplicity, robustness, and computational efficiency, it is important to acknowledge its current limitations—most of which stem directly from its core mechanism: pixel counting.
As a method based on measurable pixel occupancy within bounding shapes, GRM is inherently tied to the quality of digital segmentation, resolution, and geometric clarity.

1. **Dependence on Clean Segmentation**
   The accuracy of GRM classification depends on well-defined object boundaries. If segmentation is poor—due to noise, occlusion, or algorithmic error—the resulting pixel count may deviate significantly, leading to misclassification or uncertainty.
2. **Shape Ambiguity Near Ratio Overlaps**
   Certain shapes (e.g., ellipses, irregular blobs, or rotated hexagons) may produce pixel ratios that fall within the tolerance range of multiple GRM reference shapes. Without additional contextual information, these edge cases may remain ambiguous.
3. **No Internal Structure Analysis**
   GRM focuses purely on outer pixel coverage. It does not assess internal texture, symmetry, or center alignment—features that may be important in advanced medical, industrial, or artistic applications.
4. **Dimensional Assumptions**
   The current GRM ratios assume ideal inscribed shapes in square or cubic bounding frames. In non-orthogonal, skewed, or rotated contexts, preprocessing must first normalize orientation, which adds complexity.
5. **Not a Replacement for Full Geometry**
   GRM is designed as a complementary method, not a replacement for full analytical geometry. It excels in situations where relative proportion is more relevant than precise dimensional reconstruction. In CAD or engineering validation, GRM can guide, but not fully replace, parametric modeling.

9. Application scenarios

The GRM model's pixel-ratio approach can be applied across a wide range of domains. At the core of each scenario lies a shared principle: measuring shape identity through pixel counting within a defined frame.
This direct, resolution-independent metric enables geometric reasoning that is both lightweight and robust—whether used in education, diagnostics, AI, or engineering.

9.1 Medical imaging and diagnostics

Many medical imaging systems (e.g., MRI, CT, ultrasound) reveal circular or spherical features such as cysts, lesions, or anatomical cavities. GRM can be used to:

- Validate whether a detected shape conforms to known biological proportions;
- Provide early classification of circular anomalies based on pixel count;
- Support radiologists with a proportional, resolution-independent metric.

9.2 Geometric education tools

In educational environments, GRM allows learners to:

- Visually explore the concept of ratio using pixelated shapes;
- Build intuition for π and proportionality without abstract formulas;
- Interactively classify shapes based on how much of a square or cube they occupy.

This supports STEAM learning through hands-on geometry with immediate visual feedback.

9.3 AI post-processing validation

In AI-based segmentation pipelines, GRM acts as a lightweight decision layer:

- Confirm whether AI-generated masks actually represent canonical shapes;
- Reject outliers that deviate significantly from expected GRM ratios;
- Reduce false positives by enforcing geometric plausibility.

This can be applied in image classification, medical AI, satellite detection, and quality control.

9.4 Design and manufacturing

In product design and manufacturing, geometric accuracy is vital. GRM can:

- Check whether components (e.g., caps, connectors) conform to expected circular profiles;
- Validate printed or scanned objects in real time via vision systems;
- Serve as a geometric integrity check in automated production pipelines.

9.5 Embedded and edge applications

Because GRM requires only basic counting operations, it is ideal for:

- Embedded devices (e.g., Arduino, Raspberry Pi, Jetson Nano),
- On-device processing in drones, wearables, and smart cameras,
- Contexts with limited processing power but critical shape logic.

10. Conclusion

The Geometric Ratio Model introduces a new paradigm in digital geometry: one that abandons classical reliance on irrational constants like π in favor of fixed proportional values derived from pixel counts. By measuring how much of a square or cube a shape occupies, GRM enables a system of reasoning that is:

- **Digital-native**: rooted in the discrete structure of rasterized data;
- **Scale-invariant**: applicable at any resolution without recalibration;
- **Transparent**: based on countable quantities rather than abstract formulas;
- **Modular**: suitable for standalone tools or integration in AI pipelines.

At the heart of this method lies a simple, universal action: counting pixels within a defined frame. Whether used to validate medical imaging, educate students, classify AI-detected objects, or verify design tolerances, GRM provides a lightweight and reliable metric for shape identity in a pixelated world.

As this proposal has shown, GRM is not just a theoretical alternative to π—it is a practical instrument for geometric reasoning across fields, systems, and dimensions. By redefining measurement in terms of occupancy and ratio, the GRM method aligns perfectly with the evolving needs of digital analysis.

This is not merely a new calculation. It is a new way of seeing shapes.

10.1 The pixel as a unit of geometry

In a world defined by digital resolution, the most truthful measure is not inferred, but counted.
The pixel is not just a unit of display—it is a unit of geometry.
And by counting it, GRM redefines what it means to measure a shape.

To support and extend this approach, future versions of this proposal will include illustrative figures, worked examples, and functional software prototypes. These additions aim to enhance clarity, accessibility, and real-world applicability of the GRM pixel-ratio method.