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Mathematical Modeling for Costume Design & Fashion Technology: A Parametric Computational Framework for Contemporary Design

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***Abstract:** The fashion and costume design industry is rapidly evolving through the integration of computational tools, requiring systematic models that balance creativity with technical accuracy. This paper presents a compact mathematical framework that unifies three critical components parametric pattern generation, physics-based cloth simulation, and generative design to support modern fashion product development. The proposed model begins with a parametric geometric representation, which enables accurate and flexible pattern construction adaptable to diverse body measurements and design specifications. This mathematical layer allows for automated size grading and precise adjustment of silhouettes, thus minimizing manual intervention. The second component introduces a physics-informed simulation, where fabric behavior is modeled using measurable parameters such as elasticity, drape, and tensile strength. This ensures that virtual garments reflect real-world performance, improving both fitting accuracy and material optimization. The third component incorporates a generative aesthetic design layer, which draws upon stylistic priors and computational creativity to accelerate the exploration of new forms, textures, and patterns.*

Together, these three modules establish an end-to-end digital pipeline that integrates rapid ideation, virtual fitting, manufacturability assessment, and sustainability checks. Implementation strategies are briefly outlined, focusing on algorithmic adaptability and integration with existing computer-aided design (CAD) environments. Validation strategies suggest experimental prototyping using digital twins and virtual fashion platforms to evaluate model efficiency. Key advantages of the framework include reduction in material wastage during sampling, accelerated iteration cycles from concept to prototype, and enhanced systematic control over both aesthetic and functional constraints. By embedding mathematics into fashion workflows, the framework provides a scalable pathway for researchers, technologists, and designers seeking to align artistic innovation with efficiency, sustainability, and precision in contemporary costume and fashion technology.

***Keywords:** Mathematical framework, Costume design, Generative design, Material optimization, End-to-end digital pipeline, Virtual fitting, Material wastage reduction.*

I. INTRODUCTION

Fashion and costume design are undergoing a profound transformation as traditional craft-based methods are increasingly complemented by computational approaches. While creativity remains at the core of the discipline, technological advances have redefined how garments are conceived, developed, and tested. Recent innovations such as parametric modeling, 3D garment simulation, and generative artificial intelligence (AI) have enabled designers to prototype ideas virtually, experiment with forms, and simulate wear ability before committing to costly physical sampling. These tools are not only accelerating design cycles but also improving sustainability by reducing material waste.

Despite these advancements, the integration of computational methods is often fragmented. Parametric tools address geometric construction, while physics simulators handle fabric drape and movement, and generative AI offers aesthetic exploration. A critical gap exists in uniting these layers under a single mathematical framework that ensures scalability, repeatability, and adaptability across design contexts. For instance, pattern pieces can be represented mathematically as parametric curves and surfaces (e.g., Bézier or spline functions), fabric deformation modeled using Hooke's law and finite element analysis (FEA), while design variability can be expressed using probability distributions and optimization functions.

This paper proposes such a unified mathematical model for costume and fashion technology. The model combines (1) parametric geometry for automated pattern drafting and size grading, (2) fabric physics expressed through measurable material parameters, and (3) generative design methods informed by statistical and machine learning functions.

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The integrated approach supports faster prototyping, accurate fitting, manufacturability checks, and systematic evaluation of both functional and aesthetic qualities. By embedding mathematical reasoning into design workflows, the framework empowers both practitioners and researchers to achieve precision, efficiency, and creative diversity**,** thus bridging the gap between artistry and computation in contemporary fashion technology.

II. RELATED WORK

Recent years have seen considerable advances in the integration of mathematical and computational techniques across the fashion design pipeline. A notable example is *DiffCloth: Differentiable Cloth Simulation with Dry Frictional Contact* (Li et al., 2024) which extends traditional Projective Dynamics (PD) by introducing gradient-based methods to enable efficient inverse design and contact simulation with realistic friction. Similarly, *Inverse Garment and Pattern Modeling with a Differentiable Simulator* (Yu, Cordier & Seo, 2024) addresses the problem of recovering both 2D sewing patterns and fabric/material parameters from observed 3D draped garment shapes, ensuring the output is suitable for manufacture and realistic drape.

On the parametric pattern side, *Development of a Parametric Production Jacket Pattern for an Automated Pattern-Making System* (Kim & Park, 2025) demonstrates how silhouette and body dimensions can be encoded into formulas to automate drafting of jacket patterns, reducing time and error in traditional pattern drafting workflows. Moreover, *Automatic Generation of Parametric Patterns from Grading Patterns using Artificial Intelligence* (Oh & Kim, 2023) builds on this by using AI (neural networks) and drape simulation to produce customized patterns for off-average body shapes, showing improved fit over standard grading patterns.

Generative geometry and style guidance have also progressed: *GarmentDiffusion: 3D Garment Sewing Pattern Generation with Multimodal Diffusion Transformers* (Li, Yao & Wang, 2025) offers a diffusion transformer model capable of generating high-precision, vector sewing patterns from multimodal inputs (image, text, or partial pattern), accelerating pattern generation by orders of magnitude. Also, *Garment3DGen: 3D Garment Stylization and Texture Generation* (2024) demonstrates that 3D garment assets can be synthesized from base meshes using image guidance, then optimized (mesh deformation) such that they are simulation-ready, while preserving fabric topology and texture fidelity. These works together motivate a hybrid framework that combines (a) **geometric / parametric constraints** (e.g. pattern drafting, silhouette control), (b) **physical parameters** (fabric behavior, drape, friction, stretch), and (c) **generative priors or models** (style via image, text, or latent features) to produce garments that are not only imaginative but also manufacturable and functionally realistic.

III. PROBLEM STATEMENT & DESIGN GOALS

The growing intersection of fashion design, mathematics, and computational modeling has opened pathways for faster, more sustainable, and creative workflows. However, current solutions often exist in isolation—parametric pattern-making platforms automate drafting, physics-based simulators ensure realistic drape, and generative AI explores stylistic diversity. What is missing is a unified mathematical framework that couples these elements into a compact, modular pipeline, adaptable both for academic research and professional fashion studios.

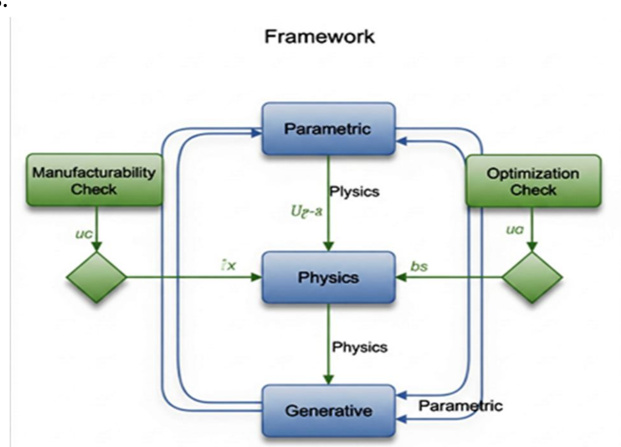

Fig 1 : Framework Architecture

Fig1 Illustrates a closed-loop design framework that integrates three core modules: Parametric, Physics, and Generative. The process is iterative, with continuous feedback from two key checks: Manufacturability and Optimization.

Existing work such as Diff Cloth (Li et al., 2024) demonstrates differentiable cloth simulation for inverse design, while Yu, Cordier & Seo (2024) show the feasibility of extracting sewing patterns and fabric parameters from 3D garments. Similarly, Kim & Park (2025) illustrate the efficiency of parametric jacket drafting systems, and Garment Diffusion (Li, Yao & Wang, 2025) highlights the potential of diffusion models for sewing pattern generation. While these advances are promising, no framework yet combines parametric geometry, fabric physics, and generative priors into a single, studio-ready tool.

To bridge this gap, we aim to design a compact mathematical model with the following goals:

1) Parametric Pattern Generation – Encode garment shapes as mathematical surfaces and curves (e.g., B-splines), supporting automated size-grading and modular reusability across multiple body dimensions.
2) Physics-Aware Fit Prediction – Incorporate material-dependent parameters (elastic modulus, bending stiffness) to predict drape and comfort using efficient finite element approximations.
3) Generative Priors for Style Variation – Employ multimodal generative models (GANs, diffusion transformers) to rapidly suggest stylistic alternatives including silhouettes, textures, and color ways.
4) Manufacturability Constraints – Integrate seam allowances, cutting layouts, and emerging methods such as digital fabric printing and 3D knitting/printing for production readiness.
5) Optimization Framework – Formulate the design process as a constrained optimization problem balancing comfort, cost, and aesthetics, solvable within practical runtime (minutes per iteration).

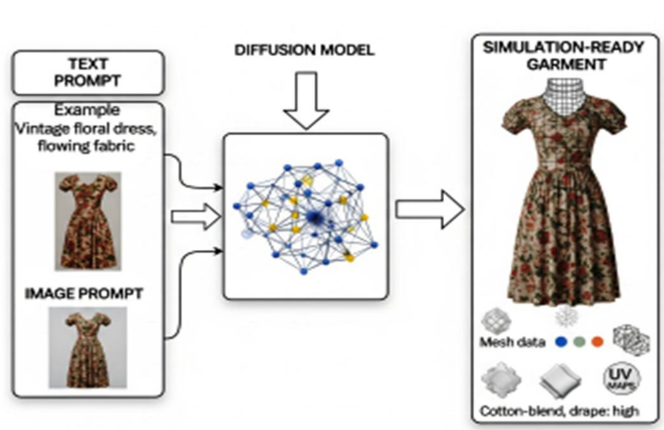

Fig2: Generative Pipeline

Fig2: This diagram illustrates a Generative Pipeline, a process that uses AI to create a digital, simulation-ready garment from a simple input. Key constraints include modularity (so pattern, physics, and generative modules can evolve independently) and computational feasibility, ensuring studio usability. This integrative approach promises not only creative flexibility but also reduced material waste and faster concept-to-sample cycles, aligning with sustainability goals.

IV. MATHEMATICAL FRAMEWORK

A. *Notation and Overview*

To formalize computational design in costume and fashion technology, we introduce a compact mathematical framework that integrates parametric geometry, cloth physics, and generative style modeling.

Let **P** represent the parametric pattern domain in 2D space, where each pattern is defined by a set of parameters $\boldsymbol{\theta} \in \boldsymbol{\Theta}$ (including lengths, curvature, and dart placement). The structural connections between panels are represented as a seam graph **S**, which ensures consistency in garment assembly. Fabric properties are modeled by **F**, capturing material behavior through a stiffness tensor **k**, bending coefficient **b**, density $\boldsymbol{\rho}$, and friction factor $\boldsymbol{\mu}$.

Generative style features are encoded as latent variables **z** from a probabilistic model such as a VAE or GAN, forming the design prior **G**. The computational pipeline proceeds in three stages:

1) Pattern generation: $\theta \rightarrow$ 2D geometry $G_2D(\theta)$.
2) Cloth simulation: $(G_2D, S, F) \rightarrow$ 3D garment mesh M_3D via a physics-based solver $\Psi(G_2D, S, F)$.
3) Stylization: $(M_3D, z) \rightarrow$ rendered design R through a mapping $\Phi(M_3D, z)$.

The optimization task is framed as a multi-objective minimization problem, seeking parameters (θ^*, F^*, z^*) that balance competing goals:

$$\theta^*, F^*, z^* = \arg\min_{\theta, F, z} \lambda_1 L_{fit}(\theta, F) + \lambda_2 L_{comf}(F) + \lambda_3 L_{aes}(M_3 D, z) + \lambda_4 L_{manuf}(\theta)$$

Here, L_{fit} measures geometric fit accuracy, L_{comf} reflects comfort and mobility, L_{aes} encodes stylistic preference, and L_{manuf} penalizes non-feasible pattern constraints. The λ terms provide tunable weights for balancing performance across functionality, aesthetics, and manufacturability, enabling modular, studio-ready workflows.

B. Parametric Pattern Model

In every pattern panel as a smooth 2D boundary expressed by parametric Bézier or B-spline curves whose control parameters are collected in

$\theta = \{ l_i, \alpha_j, r_k \}$

where l = linear scale measures (edge lengths, seam offsets), α = angular controls (corner or seam angles), and r = local curvature radii (radius or weighting terms that bias curve tightness). Each panel boundary $B(t ; \theta)$ is defined by control points derived from θ (for Bézier: direct control points; for B-splines: control vertices + knot/weight choices), so geometry is compactly editable and differentiable for optimization. Geometric constraints are enforced as low-order equalities or linear relations. Typical constraints include seam compatibility and margin consistency,

e.g. $C_{seam}(\theta) = \text{length}(\text{panelA.edge}(\theta)) - \text{length}(\text{panelB.edge}(\theta)) = 0$,

and linear margin-matching or alignment constraints. These constraints are either linear or low-order nonlinear equalities, which keeps solving efficient for interactive or batch workflows.

Size grading is handled by multiplicative scaling transforms applied per anthropometric landmark h. A base parameter set θ_{base} is transformed to size-specific parameters via diagonal

scaling operators S_{age} (or per-landmark scalars s_h):

$\theta_{size} = S_{age} \times \theta_{base}$ (or $\theta_{size}[h] = s_h \cdot \theta_{base}[h]$).

This lets designers express one base shape and generate graded variants consistent with body measurement systems.

```
control pts -> ●─●────────●────────●  (B-spline/Bézier)
                      \    /
                   \  /  α_j (angle)
                       \/
               ○  seam node (length = l_i)
                        |
              r_k (local curvature radius)
```

Fig3: schematic garment pattern generation

This constructive, parametric formulation supports both live editing (dragging α, l, r) and programmatic generation (scripting families, optimization, or batch grading). It integrates naturally with CAD pipelines that use B-splines / NURBS and with anthropometric-driven systems for individualized patterns. Recent work on automatic garment-pattern generation and spline-based parameterizations provides practical algorithms and system designs for this approach. Fig3 shows Selected recent refs: Example-based automatic garment pattern generation; Parametric automatic garment-pattern-generation (MDPI 2023); generalized Bézier-like modeling (gBS) for continuity; landmark-driven body-fit pattern generation.

C. Physics-Based Cloth Layer

We model a cloth layer using a discrete triangle mesh **M**, where each edge carries a stretching stiffness kek_eke and each vertex has mass mvm_vmv. The physical behavior is approximated through an energy formulation:

$$E_{\text{total}} = E_{\text{stretch}} + E_{\text{bend}} + E_{\text{contact}}$$

Stretching energy penalizes deviations from rest edge lengths:

$$E_{\text{stretch}} = \sum_{\text{edges}} \frac{1}{2} k_e \left(|x_i - x_j| - l_e \right)^2$$

Bending energy penalizes angular deviations between adjacent triangles:

$$E_{\text{bend}} = \sum_{\text{adjacent triangles}} \frac{1}{2} b_t (\theta_t - \theta_t^0)^2$$

Contact energy incorporates collision constraints with body or environment, ensuring non-penetration.
The equilibrium configuration of cloth corresponds to minimizing EtotalE_{\text{total}}Etotal subject to contact constraints. Modern solvers such as Projective Dynamics provide robust, fast convergence for nonlinear cloth energies. Furthermore, differentiable simulators like DiffCloth extend this to gradient-based workflows, enabling inverse design. In this setting, one specifies a target drape, fit, or garment configuration, defines a loss LfitL_{\text{fit}}Lfit between simulated and target shapes, and backpropagates gradients through the simulation to optimize material parameters (e.g., kek_eke, btb_tbt).
This differentiable framework supports automatic parameter tuning, fabric identification, and co-design of patterns and materials. It merges physical realism with machine learning and computational design, making it valuable for virtual try-on, digital prototyping, and personalized garment engineering.

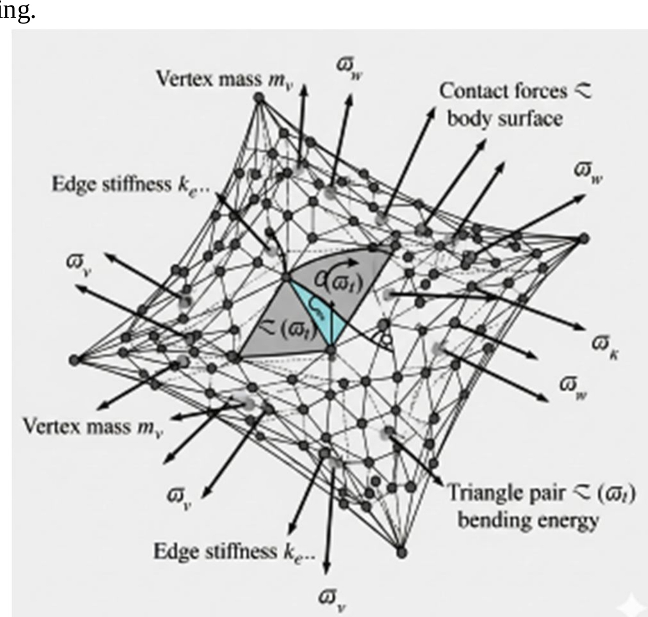

Fig4: cloth simulation and inverse design

Fig4: This diagram illustrates a common model for simulating the behavior of a deformable object, such as cloth or soft bodies, in computer graphics and physics simulations. It represents the object as a mesh of interconnected vertices, edges, and triangles.

D. Generative Aesthetic Layer

We represent style as a learned latent distribution G. Sampling from this distribution produces latent codes z~Gz \sim Gz~G, which are mapped through a decoder D(z)z) into design outputs such as texture maps, trim placements, or silhouette modifiers. This parametric decoding process allows flexible style generation while ensuring that results remain embedded in a compact latent space consistent with the training corpus.
To guide the generative process, an aesthetic loss

$$L_{\text{aes}} = d(\phi(D(z)), \phi_{\text{target}})$$

is defined between generated descriptors (e.g., color histograms, silhouette embeddings, material textures) and target style descriptors. This provides a differentiable measure of how closely a generated sample matches desired aesthetics.

At the same time, feasibility for production is ensured by integrating manufacturing constraints. For example, after generating candidates by sampling z, designs can be filtered by a manufacturability metric LmanufL_{\text{manuf}}Lmanuf. Only variants below a given threshold are retained, thereby combining creative diversity with realistic feasibility. This two-stage process (latent generation + constraint filtering) makes it possible to explore broad stylistic variations without departing from viable garment construction rules.

Recent studies demonstrate the viability of this approach. In particular, Garment3DGen and related pipelines show how generative models can translate textual or visual prompts into simulation-ready garment assets, directly bridging generative design and physically based cloth simulation. Such advances highlight how latent generative modeling, aesthetic alignment, and constraint-aware filtering together form a practical pathway for next-generation fashion CAD and digital garment creation.

V. OPTIMIZATION & IMPLEMENTATION NOTES

A. Multi-objective Optimization

Use weighted-sum or Pareto front approximation. For practical studio use, a two-step approach is efficient:

1) Coarse search in (θ, z) via surrogate models (e.g., Gaussian Process or learned emulator) that predict L_fit and manufacturability rapidly.
2) Local refinement with differentiable simulation to tune F and θ using gradient descent.

B. Accelerations & Practicalities

1) Precompute look-up tables mapping common fabric families to initial F (stiffness, bending).
2) Use low-resolution meshes for iteration; up sample for final render.
3) Leverage PM4Fashion-like scriptable parametric tools for designer control.

VI. CONCLUSION

The proposed work compact mathematical framework that unifies parametric pattern modeling**,** physics-based cloth simulation, and generative design into a single cohesive pipeline for costume and fashion design. The aim is to create a system that not only accelerates design iteration but also ensures manufacturability and creative flexibility. At the foundation, parametric pattern models encode garment panels using geometric descriptors such as lengths, angles, and curvature radii. This constructive representation makes it possible to define seams, grading rules, and size adjustments through linear or low-order nonlinear constraints. Designers can interactively manipulate these parameters, while the system guarantees geometric consistency and scalability across different body landmarks.

On top of this, physics-based cloth simulation provides realistic virtual fitting. Using triangle mesh models with stretching, bending, and contact energies, the simulator captures how fabric responds to drape, body movement, and styling. Differentiable simulation techniques further allow inverse design: material or structural parameters can be optimized to achieve a target fit or drape. This closes the loop between abstract parameters and physically grounded garment behavior.

Finally, generative design modules introduce creativity by sampling from latent style distributions. A learned decoder maps latent codes into texture maps, trim placements, or silhouette variations, while filtering mechanisms enforce manufacturability thresholds. This ensures that novel aesthetic variants remain feasible for production. Together, these three layers form an integrated framework that supports rapid ideation**,** virtual prototyping, **and** early manufacturability checks**.** By reducing reliance on physical sampling, the pipeline accelerates workflows and broadens the creative space available to designers.

The next crucial step is empirical validation**:** testing with measured fabric properties and conducting designer-in-the-loop studies. Such experiments will quantify improvements in efficiency, creative exploration, and production readiness, offering evidence of the framework's practical impact on contemporary fashion technology.

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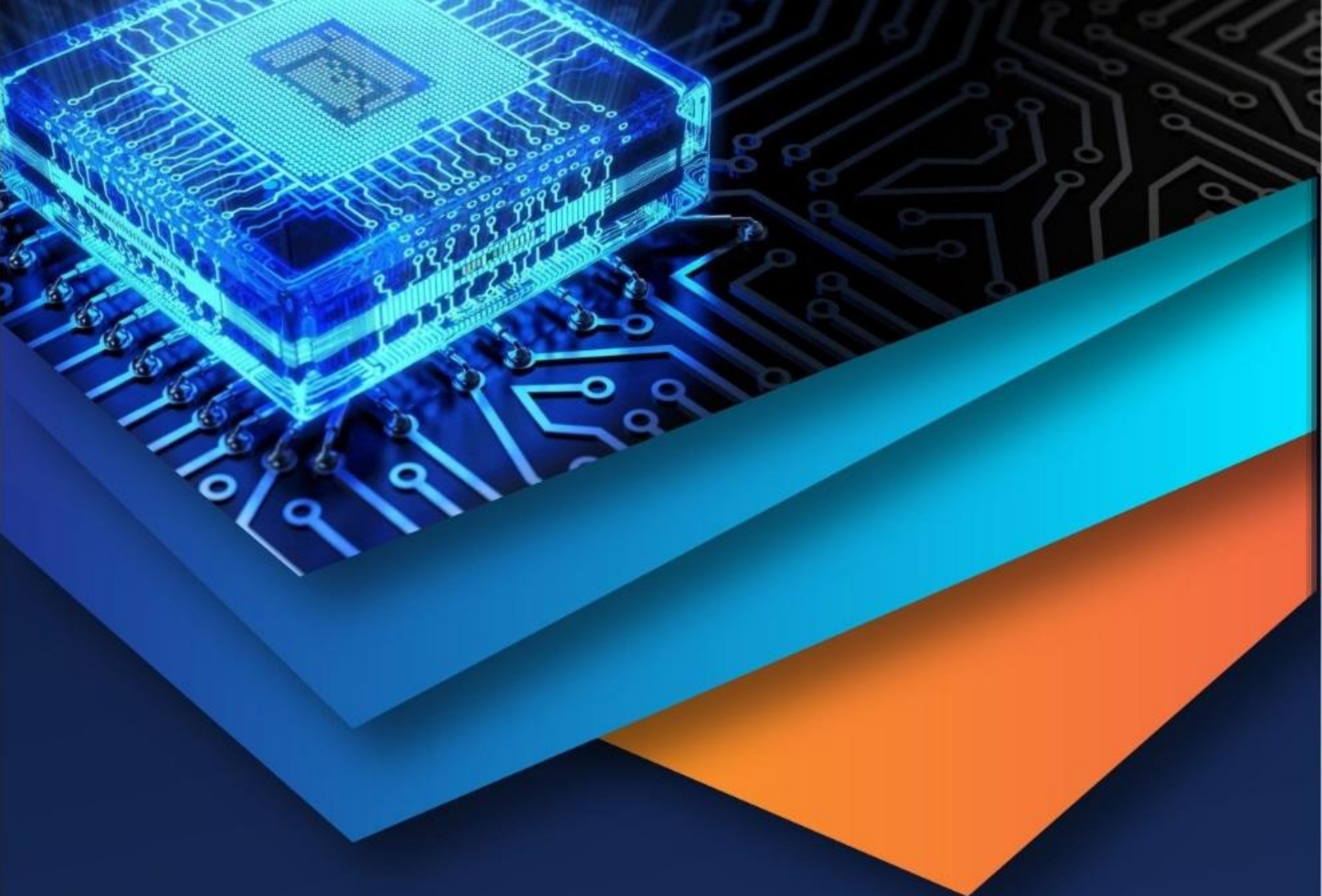

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