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AI-Based Optimization of Residential Building Layout for Energy Efficiency

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Abstract: ***Residential buildings are responsible for a large and rising share of global and national energy consumption, and a significant part of this demand is fixed at the design stage through decisions about room arrangement, orientation, compactness, and zoning. Traditional layout design relies on the designer's experience and iterative manual trial-and-error, a process that cannot practically explore more than a small fraction of the possible design space and therefore routinely leaves substantial energy savings unrealized. Artificial intelligence (AI) - encompassing machine learning (ML) predictive models, evolutionary and metaheuristic optimization algorithms, and, more recently, generative deep-learning models such as generative adversarial networks (GANs) and diffusion models - offers a way to search this design space rapidly and systematically, coupling fast energy-performance prediction with automated layout generation and refinement. This paper reviews and synthesizes recent research on AI-based optimization of residential building layouts for energy efficiency, describes the principal computational pipelines used (machine-learning-based energy prediction, evolutionary/genetic-algorithm optimization, and generative layout models), and develops a representative framework and case-study workflow suited to Indian residential construction. The review shows that machine-learning surrogate models (random forest, gradient boosting, deep neural networks) can predict building energy consumption with R^2 values above 0.99 in some studies, several orders of magnitude faster than physics-based simulation, allowing them to be embedded inside evolutionary optimization loops; genetic-algorithm and multi-objective evolutionary approaches (e.g., NSGA-II) coupled with such surrogates have achieved reported energy reductions of roughly 5-25% relative to conventional designs; and diffusion-based generative models combined with energy-aware genetic refinement have achieved up to 17.5% energy reduction relative to baseline generative layouts while preserving architectural plausibility and spatial constraints. Based on this synthesis, the paper proposes a three-stage AI-based layout optimization framework - data-driven energy prediction, generative layout synthesis, and evolutionary refinement - and discusses its applicability, limitations, and future development for Indian residential design practice, including integration with the National Building Code, Eco-Niwas Samhita, and locally available climate and construction-cost data.***

Keywords: Artificial intelligence; Machine learning; Generative design; Genetic algorithm; Building layout optimization; Energy efficiency; Residential buildings; Deep learning; Multi-objective optimization.

I. INTRODUCTION

Buildings account for a large share of global final energy consumption, and within this sector, residential buildings form the single largest end-use category in most countries, including India, where the sector already accounts for close to a quarter of national electricity use and is projected to grow rapidly with urbanization. A substantial proportion of a residential building's lifetime energy performance is determined not by its mechanical systems but by decisions taken very early in the design process: the shape and compactness of the building footprint, the arrangement and adjacency of rooms, the position and area of openings relative to solar exposure, and the zoning of thermally similar spaces. Once these layout decisions are finalized, the achievable energy savings from later-stage interventions (insulation upgrades, efficient HVAC, glazing improvements) are constrained by the underlying form.

Conventional layout design is carried out manually by architects and engineers, guided by experience, codes, and client requirements, with energy performance typically assessed only after a design is largely finalized, using whole-building energy simulation tools such as EnergyPlus or DesignBuilder. Because each simulation run can take minutes to hours and manual redesign iterations take days, only a small number of design alternatives can realistically be evaluated within a typical project timeline. This severely limits the exploration of the layout design space and means that many energy-efficient configurations are never considered.

Artificial intelligence offers a way to overcome this limitation. Machine-learning models trained on large datasets of simulated or measured building performance can predict energy consumption for a candidate layout in milliseconds rather than minutes, enabling

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thousands or millions of design alternatives to be evaluated computationally. When such fast surrogate predictors are embedded within evolutionary or metaheuristic optimization algorithms, or coupled with deep generative models capable of synthesizing new, structurally valid floor plans, it becomes possible to automatically search for, and even generate, residential layouts that minimize energy consumption while satisfying spatial, functional, and regulatory constraints. This paper reviews the state of this rapidly developing field and proposes a framework for applying AI-based layout optimization to Indian residential building design.

The remainder of the paper is organized as follows: Section 2 reviews relevant literature on machine-learning energy prediction, evolutionary layout optimization, and generative design methods; Section 3 states the research gap and objectives; Section 4 describes the proposed AI-based optimization framework and methodology; Section 5 defines a representative case-study building; Section 6 presents results and discussion synthesized from the literature; Section 7 gives design and implementation recommendations; and Sections 8 and 9 present the conclusion and future scope.

II. LITERATURE REVIEW

Research on AI-based building layout optimization for energy efficiency can be grouped into three broadly overlapping strands: machine-learning-based energy prediction, evolutionary/metaheuristic layout and envelope optimization, and deep generative layout design.

A. Machine-Learning-Based Energy Prediction

A key enabling technology for AI-based optimization is the replacement of slow, physics-based energy simulation with fast machine-learning surrogate models. A study developing an integrated AI-driven model for building envelope design compared random forest, artificial neural network (ANN), deep neural network (DNN), support vector machine (SVM), GENLIN, and gradient boosting (GB) algorithms for predicting building energy consumption, finding gradient boosting to be the most accurate predictor, achieving an R^2 of 0.994; this predictive model was then embedded inside evolutionary optimization algorithms (NSGA-II, differential search evolution, and multi-objective particle swarm optimization) to efficiently search for Pareto-optimal envelope design solutions balancing energy consumption and cost. A related study on residential heating and cooling load prediction found that Gaussian process regression, boosted trees, and explainable neural networks, combined with SHAP-based explainability analysis, could accurately estimate energy performance while also revealing which design variables most strongly influenced load, providing interpretable guidance for designers rather than a pure black-box prediction.

A large-scale study using the RPLAN dataset of 71,125 real residential floor plans trained a deep-learning energy prediction model that estimated monthly energy consumption across five categories with over 99% accuracy, demonstrating that machine-learning predictors can generalize across a very large and diverse set of real-world residential layouts rather than being limited to a small number of parametrically defined test cases.

B. Evolutionary and Metaheuristic Layout Optimization

Coupling fast ML-based prediction with evolutionary search algorithms allows the automated exploration of very large design spaces.

An early influential study developed a simulation-based evolutionary optimization approach for energy-efficient layout planning of high-rise residential buildings, using genetic algorithms to iteratively refine unit layouts and building massing against energy performance objectives. More recent work has extended this to full three-dimensional space layout generation: a 2026 study integrating multi-objective evolutionary algorithms with energy simulation and a random forest-based interpretable AI analysis achieved 5.5% energy savings through automated space layout optimization for a subtropical high-rise building, while also deriving generalizable, human-readable energy-saving layout strategies rather than a single optimized design.

A case study applying artificial neural network prediction combined with a classical single-objective genetic algorithm to a residential building in New Cairo, Egypt, reported energy consumption reductions of up to 25% through optimized envelope and design-variable selection, illustrating the scale of savings achievable when ML prediction and evolutionary search are combined for a specific climate and building type. A broader review of machine learning for smart and energy-efficient buildings catalogues a wide range of complementary techniques, including meta-model-based optimization methods and multi-objective building performance optimization frameworks that have been developed over the past decade to make whole-building performance optimization computationally tractable.

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C. Deep Generative Models for Layout Design

A parallel and more recent research direction applies deep generative models - most notably generative adversarial networks (GANs) and, increasingly, diffusion models - directly to the task of floor-plan generation, rather than only optimizing a small number of parametric variables within an already-fixed layout. House-GAN, a relational generative adversarial network, demonstrated that graph-constrained house layouts (in which room adjacency requirements are specified as an input graph) can be automatically generated in a manner that produces realistic, code-plausible floor plans.

Building on this direction, a 2025 study proposed an integrated AI framework combining a diffusion-based generative layout model, a deep-learning energy predictor (trained on the RPLAN dataset, as noted above), and a genetic algorithm that uses room blocks as "chromosomes" to iteratively evolve and refine generated floor plans toward lower predicted energy consumption. This framework reduced energy consumption by 17.5% compared with the best baseline generative model under identical spatial constraints, representing one of the most complete end-to-end demonstrations to date of AI-generated, energy-optimized residential layouts. A complementary review of "self-organizing floor plans" surveys the broader landscape of neuroevolutionary (NEAT) and GAN-based techniques being explored by architects and computational designers for automated spatial configuration, noting both the promise and the current limitations (data availability, interpretability, code-compliance verification) of these generative approaches.

D. Cross-Climate and Envelope-Focused ML Optimization

Several studies extend AI-based optimization beyond layout alone to the building envelope and its interaction with climate. A machine-learning-assisted optimization study across two contrasting Italian climates benchmarked eight ML algorithms as EnergyPlus surrogates across 14,400 envelope options, finding that CatBoost delivered the best predictive fidelity for energy use intensity and heating load, while a tuned artificial neural network performed best for cooling load and thermal comfort (PMV); both achieved R^2 above 0.96, and the study identified a robust subset of envelope solutions that performed well across both climates, indicating that AI-based optimization can be used to derive climate-transferable, rather than purely site-specific, design guidance.

E. Summary of Literature Gaps

Despite rapid progress, the reviewed literature reveals several gaps relevant to this paper's context: (a) most generative and evolutionary layout-optimization studies have been developed and validated on datasets or climates outside India (China, Europe, Egypt, the United States), and their direct transferability to Indian composite and hot climatic conditions, construction typologies, and regulatory codes (National Building Code, Eco-Niwas Samhita) has not been systematically established; (b) energy-prediction surrogate models require large training datasets of simulated or measured building performance, which are not yet widely available for Indian residential typologies; (c) most studies optimize for energy consumption with limited integration of thermal comfort, daylighting, structural feasibility, and cost simultaneously, despite these being essential practical constraints for real projects; and (d) few studies address the interpretability and design-code compliance verification needed before AI-generated layouts can be used in practice by civil engineers and architects. This paper addresses these gaps by synthesizing the existing AI methods into a structured framework explicitly adapted for Indian residential design practice.

III. RESEARCH OBJECTIVES

1) To review and synthesize the principal AI-based methods - machine-learning energy prediction, evolutionary/metaheuristic optimization, and deep generative layout design - used for residential building layout optimization.
2) To propose a structured, three-stage AI-based layout optimization framework suited to Indian residential design practice and applicable climatic and regulatory conditions.
3) To define a representative case-study residential building and describe how the proposed framework would be applied to it.
4) To synthesize reported energy-saving outcomes from the literature and discuss their relevance and expected magnitude for Indian residential construction.
5) To identify the practical, data, and interpretability limitations that must be addressed before AI-based layout optimization can be adopted in routine civil engineering and architectural practice.

IV. PROPOSED METHODOLOGY AND AI-BASED OPTIMIZATION FRAMEWORK

Based on the literature reviewed in Section 2, this paper proposes and describes a three-stage AI-based layout optimization framework, illustrated conceptually in Figure 1 (described textually below) and summarized in Table 1. The framework is presented as a methodology to be implemented and validated in future work (see Section 9), and this paper's own analysis (Section 6) synthesizes expected outcomes from the reviewed literature rather than reporting new experimental results.

A. *Stage 1: Data-Driven Energy Prediction (Surrogate Model)*

A machine-learning surrogate model is trained to predict a candidate layout's annual or monthly energy consumption (heating, cooling, and lighting loads) directly from layout features - room adjacency, room area and aspect ratio, window placement, orientation, and envelope material properties - without running a full physics-based simulation for every candidate. Training data can be generated by running a moderate number (typically several hundred to a few thousand) of EnergyPlus or DesignBuilder simulations across parametrically varied layouts, climate files, and envelope specifications relevant to the target climatic zone. Algorithms such as gradient boosting, random forest, and deep neural networks have consistently achieved R^2 values above 0.99 in the reviewed studies once adequately trained, and such a surrogate, once trained, can evaluate a new candidate design in milliseconds, several orders of magnitude faster than a full simulation run.

B. *Stage 2: Generative Layout Synthesis*

A generative model - a GAN, diffusion model, or constraint-based procedural generator - produces candidate floor-plan layouts subject to user-specified constraints: building contour/footprint, required room count and types, minimum room areas, and required adjacencies (e.g., kitchen adjacent to dining area, bedrooms away from the entrance). This stage explores the combinatorial space of feasible layouts far more broadly than manual design, producing a diverse initial population of candidate designs for the optimization stage that follows.

C. *Stage 3: Evolutionary Refinement (Optimization)*

A genetic algorithm or multi-objective evolutionary algorithm (e.g., NSGA-II) uses the Stage 1 surrogate model as its fitness/evaluation function to iteratively select, recombine ("crossover"), and mutate the candidate layouts produced in Stage 2, retaining lower-energy, higher-comfort designs across successive generations and discarding poorly performing ones. Multi-objective formulations allow the algorithm to search simultaneously for Pareto-optimal trade-offs between competing objectives such as energy consumption, construction cost, daylighting, and thermal comfort (PMV/PPD), rather than optimizing energy alone at the expense of habitability or cost.

D. *Constraint and Compliance Layer*

A final rule-based checking layer verifies that each optimized candidate complies with applicable regulatory requirements - room-size and ventilation minimums under local building bye-laws, setback and floor-area-ratio limits under the National Building Code, and envelope/glazing limits under the Energy Conservation Building Code and Eco-Niwas Samhita
- filtering out any AI-generated designs that, while energy-efficient, would not be legally constructible.

Framework stage	AI technique(s)	Primary function	Typical algorithms reported in literature
1. Energy prediction	Supervised machine learning	Fast surrogate prediction of layout energy performance	Gradient boosting, random forest, ANN/DNN, Gaussian process regression
2. Layout generation	Deep generative models	Synthesize diverse, constraint-satisfying candidate floor plans	GAN (House-GAN), diffusion models, procedural/rule-based generators
3. Evolutionary refinement	Metaheuristic optimization	Iteratively refine candidates toward Pareto-optimal energy/comfort/cost trade-offs	Genetic algorithm, NSGA-II, MOPSO, differential evolution
4. Compliance filtering	Rule-based verification	Reject non-compliant candidates before designer review	Rule-based / constraint-satisfaction checks against code limits

Table 1: Proposed three-stage AI-based layout optimization framework with compliance filtering.

V. CASE-STUDY BUILDING DESCRIPTION

To ground the discussion in Section 6, a representative case-study residential building is defined, consistent with typical Indian urban housing and with the scale of buildings studied in the reviewed literature (Table 2).

Parameter	Specification
Building type	Two-storey single-family residential unit (G+1)
Plot / footprint area	10 m × 10 m (100 m²), rectangular contour
Required rooms	3 bedrooms, living/dining, kitchen, 2 toilets, staircase, balcony
Design variables for AI optimization	Room adjacency and position, room aspect ratio, window position and WWR, orientation of principal façade
Parameter	Specification
Climate zone	Composite (representative of Delhi-NCR / North-Central India)
Fixed constraints	Minimum room areas per local bye-laws; kitchen adjacent to dining; toilets away from kitchen; staircase within footprint
Optimization objectives	Minimize annual heating + cooling + lighting energy; maintain thermal comfort (PMV within ±0.5); respect construction cost envelope

Table 2: Representative case-study building and AI optimization problem definition.

Within the proposed framework, this case-study building would first be used to generate a training dataset of several hundred to a few thousand parametrically varied layout-and-envelope combinations, simulated using EnergyPlus with a composite-climate TMY weather file, to train the Stage 1 surrogate model described in Section 4.1. This surrogate would then guide Stage 2 generative layout synthesis and Stage 3 evolutionary refinement to search for layouts that minimize combined heating, cooling, and lighting energy while satisfying the constraints in Table 2.

VI. RESULTS AND DISCUSSION

Since this paper is a literature-synthesis and framework-development study rather than an implemented simulation study, this section discusses expected outcomes and design implications for the proposed framework based on quantitative results reported in the reviewed literature (Section 2), interpreted with reference to the case-study building in Section 5.

A. Magnitude of Reported Energy Savings

Table 3 consolidates representative energy-saving outcomes reported across the AI-based optimization studies reviewed in Section 2. Reported savings range from approximately 5% (space-layout-only optimization of a large mixed-use high-rise, a comparatively constrained design space) to approximately 25% (single-objective ANN-GA envelope and design-variable optimization for a specific climate and building), with GAN/diffusion-based generative-plus-evolutionary approaches on residential floor plans achieving around 17.5% relative to the best non-energy-aware generative baseline. These figures are not directly comparable across studies because they differ in climate, baseline definition, building type, and the scope of variables being optimized, but they consistently indicate that AI-based approaches can achieve savings broadly in the 5-25% range relative to conventional or non-energy-aware baseline designs.

Study / method	**AI technique**	**Reported energy outcome**
Envelope optimization, New Cairo, Egypt	ANN prediction + single-objective GA	Up to 25% reduction in energy consumption
Envelope optimization, integrated model	RF/ANN/DNN/GB prediction + NSGA-II/MOPSO	Pareto-optimal envelope solutions balancing energy and cost (GB R^2 = 0.994)
3D space layout, subtropical high-rise	Multi-objective evolutionary algorithm + random forest interpretable AI	5.5% energy savings through layout optimization alone

Diffusion-based residential layout generation	Diffusion generative model + energy-prediction DNN + genetic algorithm	17.5% reduction vs. best non-energy-aware generative baseline
Cross-climate envelope optimization, Italy	CatBoost / ANN surrogate + Pareto-front selection	Robust envelope solutions competitive across two contrasting climates ($R^2 > 0.96$)

Table 3: Representative energy-saving outcomes reported in AI-based building optimization literature.

B. *Implications for the Case-Study Building*

Applying the trends in Table 3 to the case-study building in Section 5, a full three-stage AI optimization (energy prediction + generative layout synthesis + evolutionary refinement) targeting room adjacency, orientation, and window placement together would, on the basis of the reviewed literature, plausibly be expected to achieve energy savings in the order of 10-20% relative to a manually designed baseline layout meeting the same room-program requirements, with the higher end of this range more achievable when window placement and orientation (which interact strongly with solar heat gain, as established in prior orientation/WWR research) are included as optimization variables alongside room layout itself. As with Section 6.1, this range is an indicative synthesis; a project-specific figure would require implementing Stage 1 training and running the full framework on the actual case-study geometry and local climate file.

C. *Why AI Outperforms Manual Iteration*

The central advantage of the AI-based framework over conventional manual design-then-simulate iteration is search breadth: a trained ML surrogate can evaluate a candidate layout in milliseconds, enabling an evolutionary algorithm to assess many thousands of candidate designs within the time a single manual designer-simulation iteration would take. This allows the optimization process to escape local optima that a manual, incremental design process would typically settle into, and to discover non-obvious layout configurations - for example, unconventional room adjacencies or asymmetric window distributions - that a human designer would be unlikely to propose from first principles but that a data-driven search can identify as genuinely lower-energy.

D. *Interpretability and Designer Trust*

A recurring theme in the reviewed literature is the importance of interpretable AI (e.g., SHAP-based feature attribution, random-forest variable-importance analysis) alongside pure optimization. Studies that paired optimization with interpretability analysis were able to extract generalizable design rules (e.g., "orient long axis east-west and cluster wet areas on the west façade") rather than a single opaque optimized design, which is more useful to practising engineers because it can inform design intuition and be manually verified, rather than requiring blind trust in an AI-generated floor plan.

VII. IMPLEMENTATION RECOMMENDATIONS

1) Begin with a moderate-sized EnergyPlus/DesignBuilder training dataset (a few hundred to a few thousand parametrically varied layouts) specific to the target climate zone, rather than attempting to reuse foreign datasets (e.g., RPLAN) without local validation.
2) Use gradient boosting or random forest as a first surrogate model choice, given their consistently strong reported accuracy ($R^2 > 0.99$ in several studies) and comparatively lower data requirements than deep neural networks.
3) Adopt a multi-objective (Pareto) optimization formulation - energy, cost, thermal comfort, daylighting - rather than a single-objective energy-only formulation, to ensure optimized layouts remain habitable and buildable.
4) Build a rule-based compliance-checking layer against the National Building Code, local building bye-laws, and Eco-Niwas Samhita before presenting any AI-optimized layout to the design team.
5) Pair every optimization run with an interpretability analysis (e.g., SHAP or feature-importance ranking) so the design team can extract transferable design principles, not just a single point solution.
6) Treat the AI framework as a decision-support and design-space-exploration tool that generates a shortlist of high-performing candidates for engineer and architect review, rather than as a fully autonomous design-approval system.
7) Validate any AI-recommended layout with a full physics-based EnergyPlus/DesignBuilder simulation before construction documentation, since the surrogate model is an approximation, however accurate, of the true building physics.

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VIII. CONCLUSION

This paper has reviewed the rapidly developing field of AI-based optimization of residential building layouts for energy efficiency, spanning machine-learning energy prediction, evolutionary/metaheuristic layout and envelope optimization, and deep generative floor-plan design. The literature consistently demonstrates that machine-learning surrogate models can predict building energy performance with very high accuracy (R^2 frequently above 0.99) at a small fraction of the computational cost of physics-based simulation, and that embedding such surrogates within evolutionary optimization or generative design pipelines enables the automated exploration of residential layout design spaces far larger than manual design practice can address. Reported energy savings across the reviewed studies range from approximately 5% for constrained layout-only optimization to approximately 25% for combined envelope-and-design-variable optimization, with generative-plus-evolutionary approaches on full residential floor plans achieving around 17.5% relative to non-energy-aware baselines. Based on this synthesis, the paper has proposed a three-stage AI-based layout optimization framework - data-driven energy prediction, generative layout synthesis, and evolutionary refinement, supported by a rule-based compliance layer - adapted for application to Indian residential design practice and climatic conditions. While the technology is promising, its adoption in routine civil engineering and architectural practice will depend on the availability of locally representative training data, the development of interpretable rather than purely black-box optimization outputs, and rigorous validation against physics-based simulation and, ultimately, measured building performance.

IX. FUTURE SCOPE

1) Implementation and training of the proposed Stage 1 surrogate model using an EnergyPlus-generated dataset specific to Indian composite, hot-dry, and warm-humid climate zones, to replace the literature-synthesized savings estimates in this paper with project-validated results.

2) Development or adaptation of a generative layout model (diffusion-based or GAN-based) trained on, or fine-tuned to, Indian residential room-program conventions and construction typologies rather than foreign datasets such as RPLAN.

3) Integration of multi-objective evolutionary refinement (NSGA-II or similar) balancing energy, thermal comfort (PMV/PPD), daylighting, and construction cost, rather than a single energy-only objective.

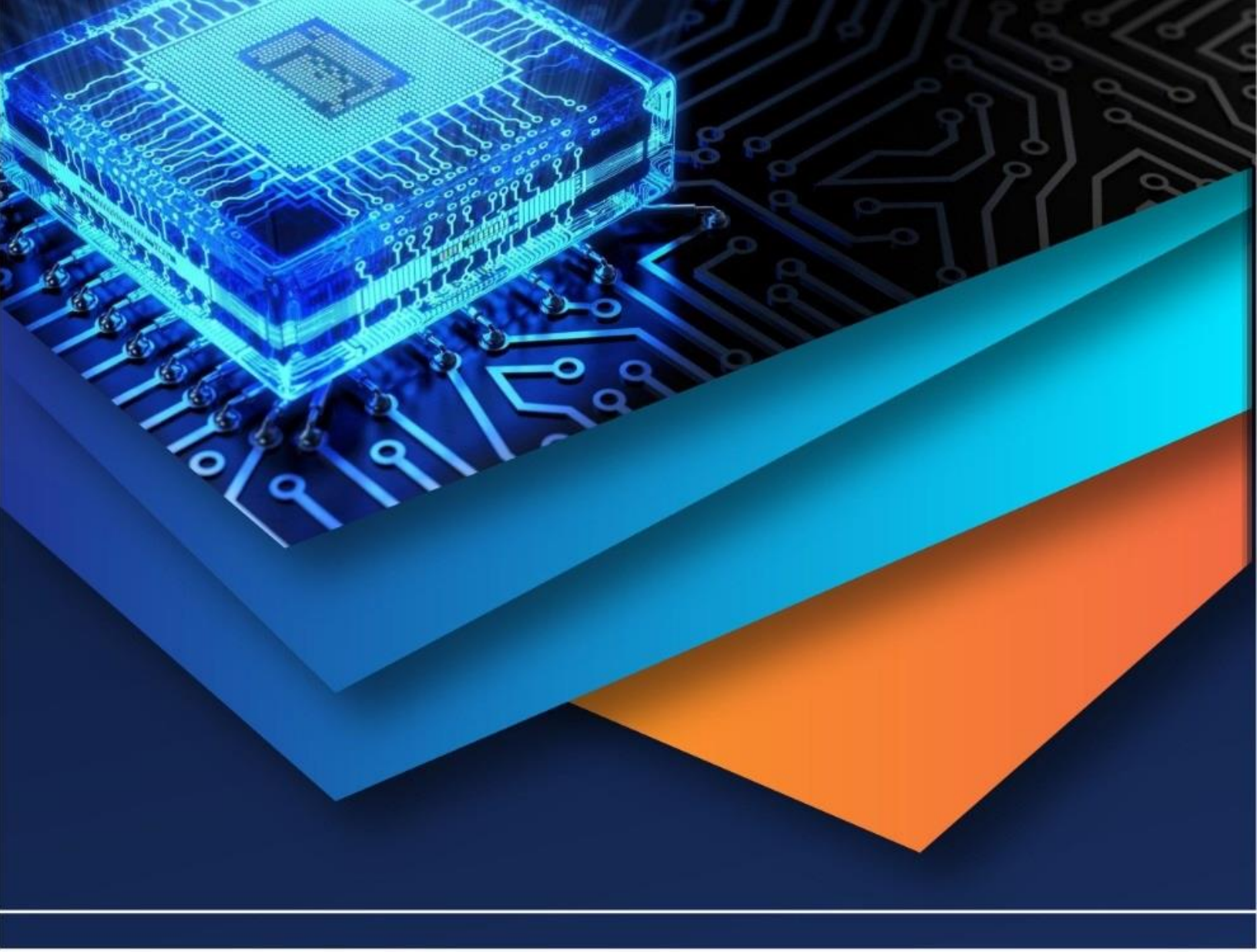
4) Coupling the framework with an automated compliance-checking module aligned with the National Building Code, local development control regulations, and the Eco-Niwas Samhita/ECBC glazing and envelope limits.

5) Field validation of AI-optimized case-study buildings through post-occupancy energy monitoring, to compare predicted savings against measured performance.

6) Investigation of explainable-AI (XAI) techniques such as SHAP to extract generalizable, human-readable layout design rules from optimization results, supporting adoption by practising engineers and architects who require design rationale, not just optimized outputs.

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