



# A HYBRID COMPUTATIONAL FRAMEWORK FOR INTERIOR DESIGN COST PREDICTION INTEGRATING CNN-BASED STYLE CLASSIFICATION AND BLUEPRINT ANALYSIS

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**Abstract:** Accurate cost estimation in interior design is a complex challenge characterized by high-dimensional variables and subjective aesthetic choices. Traditional estimation methods often suffer from significant margins of error due to the non-linear relationship between spatial configurations and material costs. This paper proposes a hybrid computational framework that integrates traditional Machine Learning (ML) with Deep Learning for enhanced predictive accuracy. A dual-input pipeline is employed: first, a Convolutional Neural Network (CNN) extracts design features and material styles from 2D architectural blueprints; second, these visual features are fused with structured tabular data—such as square footage, geographical location, and material grades—to feed ensemble learning models including Random Forest and XGBoost. Experimental results demonstrate that the hybrid framework achieves a Mean Absolute Error of 6.14%, representing a significant improvement over traditional baseline model. The study concludes that the synergy of computer vision and regression-based ML provides a robust, scalable tool for real-time budgetary forecasting in the architectural and interior design industries.

**Index Terms** - Interior Design, Cost Estimation, Cost Prediction, Machine Learning, Computer Vision, Convolutional Neural Network, Deep Learning, XGBoost, Random Forest, Blueprint Analysis.

## I. INTRODUCTION

Interior design plays a vital role in enhancing the functionality, usability, and aesthetic quality of built environments. Effective interior design not only improves visual appeal but also optimizes space utilization, comfort, and operational efficiency in both residential and commercial projects. As interior design projects increase in scale and complexity, accurate cost estimation during the early planning phase has become a critical requirement for successful project execution.

Despite its importance, early-stage cost estimation in interior design remains a challenging task. Conventional estimation techniques primarily rely on manual interpretation of architectural blueprints and the expertise of design professionals. Such approaches are often labor-intensive, subjective, and susceptible to human error, particularly when dealing with complex layouts or frequent design revisions. Inaccurate estimates at the planning stage may lead to budget overruns, inefficient resource allocation, and reduced client satisfaction.

Recent advancements in computer vision and machine learning have enabled automated analysis of visual and structural data, offering new opportunities for improving cost estimation accuracy. Computer vision techniques extract quantitative features from architectural blueprints—such as spatial dimensions, room configurations, and structural components. When combined with machine learning models trained on historical cost data, these features enable data-driven prediction of interior design costs with improved reliability and consistency.

In this paper, an AI-driven framework is proposed for predicting interior design costs by integrating blueprint-based feature extraction with machine learning-based cost modelling. The proposed system aims to deliver precise, unbiased, and transparent cost estimations that support informed decision-making during the early stages of project planning. By reducing dependency on manual estimation and expert intuition, the framework assists designers and clients in achieving data-driven, budget-conscious interior design decisions.

## II. LITERATURE REVIEW

The evolution of cost estimation in interior design has progressed through three distinct eras: traditional manual estimation, algorithmic BIM-integrated forecasting, and modern AI-driven predictive modelling.

Historically, interior design costs were estimated using manual "take-off" methods where quantities were extracted from 2D blueprints and multiplied by unit rates. However, this method is highly susceptible to human error and fails to account for market volatility. The introduction of 5D Building Information Modelling (BIM) automated some of these processes by linking 3D geometries directly to cost databases. Despite this automation, BIM-based tools remain deterministic; they can calculate "known" quantities but struggle to predict "hidden" costs associated with design complexity, labor specialized for specific aesthetics, and non-linear material wastage.

To address the limitations of deterministic models, researchers have applied various Machine Learning (ML) techniques. Ensemble methods, particularly Random Forest (RF) and XGBoost, have become the industry standard for processing tabular project data. Hybrid ML models can achieve predictive accuracies exceeding 92% by identifying correlations between project duration, floor area, and material grades [1]. However, these models are limited by their reliance on numerical inputs, often ignoring the "visual" complexity of a design, which significantly influences final pricing.

The most recent shift involves the use of Convolutional Neural Networks (CNN) to interpret the visual components of design. Research into style classification using architecture has proven that AI can quantify aesthetic elements previously considered subjective [4]. In 2024, studies integrated Computer Vision with CAD systems to assess spatial layouts and color palettes automatically.

While existing literature covers ML for numerical cost prediction and CNN for style classification independently, there is a notable scarcity of research that fuses these two domains. This paper addresses this gap by proposing a multi-model framework that extracts visual features via a CNN and integrates them with tabular ML regressors to provide a holistic and highly accurate cost forecasting tool.

## III. METHODOLOGY

### A. System Architecture and Workflow

The proposed framework is a hybrid system that bridges computer vision and structural estimation. The architecture is divided into three distinct modules: (1) The Vision Module—CNN-based style identification; (2) The Geometric Module—blueprint parsing and area calculation; and (3) The Analytical Module—cost synthesis and statistical validation. Input data flows from the blueprint image and structured parameters through the dual pipelines, with features merged before the final ensemble regression stage.

### B. CNN-Based Style Classification

The cost of interior design is heavily non-linear, dictated more by aesthetic complexity than by raw area alone. To quantify this, a deep CNN is employed to categorize design styles (e.g., Modern, Industrial, Minimalist, Victorian) from interior room images.

The CNN architecture comprises: (i) an Input Layer that accepts RGB images resized to 224×224 pixels; (ii) four Feature Extraction blocks, each consisting of 3×3 convolutional kernels, batch normalization, and ReLU activations to capture stylistic textures; (iii) Max-Pooling layers (2×2 stride) between blocks for dimensionality reduction; and (iv) a Classification Head with Dropout (p=0.5) and a SoftMax output layer providing probability distributions across N design styles. The model was trained on approximately 3,000

annotated interior images covering 18 distinct style categories with roughly 600 images per class, ensuring balanced representation.

Instead of using only the final classification output, the dense feature vector from the penultimate layer is extracted and used as a high-dimensional embedding representing the spatial and aesthetic complexity of the input image. This embedding is subsequently concatenated with structured tabular features for the final regression stage.

### C. Blueprint Processing and Feature Extraction

Upon user upload, a 2D blueprint undergoes several image pre-processing transformations: Grayscale Transformation removes color noise to focus on structural lines; Bilateral Filtering smooths the image while preserving wall and door edges; and Canny Edge Detection identifies structural boundaries across the floor plan.

Room identification is achieved through: Contour Approximation using the Satoshi Suzuki algorithm to detect closed polygonal shapes; Optical Character Recognition (OCR) to identify text labels (e.g., "Kitchen", "Bedroom") and assign cost-per-square-foot rates to specific zones; and Pixel-to-Metric Ratio scaling calibrated from a user-supplied reference dimension to calculate precise room areas in square feet.

Structured tabular features extracted include: Total Area (sq. ft.), Quality Grade (Economy / Standard / Premium), Geographical Location (influencing labour and transport costs), and Material Type (specifying flooring, cabinetry, and fixture categories). These are pre-processed through normalization and one-hot encoding before fusion.

### D. Ensemble Regression for Cost Prediction

The fused feature vector—comprising CNN visual embeddings and structured tabular attributes—is fed into two ensemble regression models: Random Forest Regressor and Extreme Gradient Boosting (XGBoost). These models are selected for their ability to handle high-dimensional inputs, resist overfitting, and effectively model non-linear cost relationships. The Thane reference estimator framework is applied to generate cost breakdowns across Civil & Finishing, Furniture, Electrical, and Contingency (5%) categories. Final predictions are validated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared ( $R^2$ ) metrics.

## IV. RESULTS AND DISCUSSION

### A. Deployed System Interface

The proposed system was deployed as an interactive web application with a three-panel interface. The left panel accepts the blueprint image upload along with structured inputs (carpet area, design style, and material grade). The center panel provides a real-time blueprint preview upon upload. The right panel displays the complete predicted cost breakdown including Civil & Finishing, Furniture, Electrical, and Contingency components, along with extracted image analytics such as edge density and line ratio derived from the blueprint.

### B. Blueprint-Based Cost Prediction Results

The system was tested across multiple real-world blueprint inputs with varying areas and material grades. The following figures illustrate the detailed cost report outputs generated by the framework for each blueprint, demonstrating the model's ability to adapt its predictions to spatial complexity and quality grade.

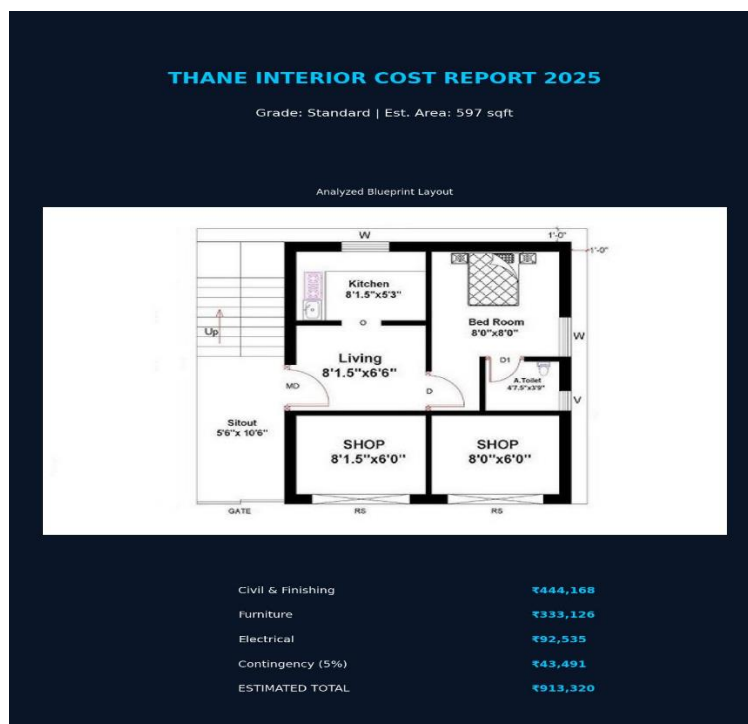


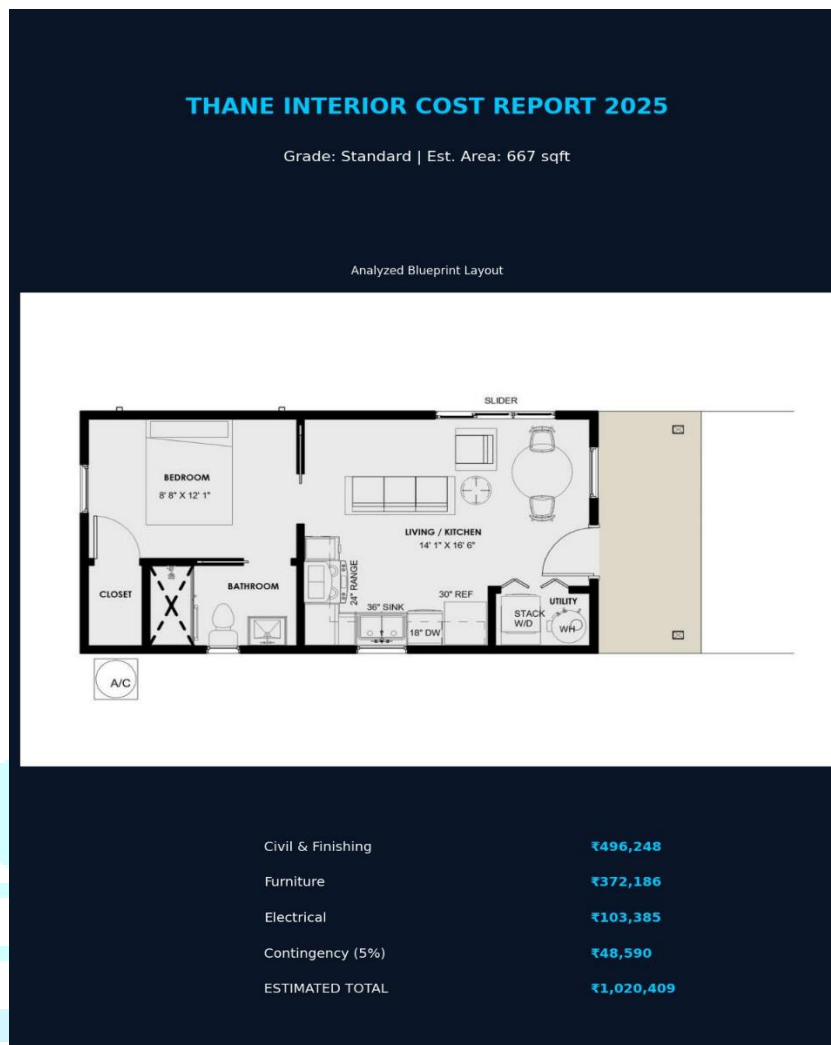
Figure 1. Cost Report – 597 sq. ft. Blueprint, Standard Grade (Estimated Total: ₹9,13,320)

Fig. 1 presents the prediction for a 597 sq. ft. layout at Standard grade. The framework identified key room components (Kitchen 8'x5', Bedroom 8'x8', Living 8'x6.5', two Shop units) from the blueprint and returned an estimated total of ₹9,13,320, decomposed as Civil & Finishing (₹4,44,168), Furniture (₹3,33,126), Electrical (₹92,535), and Contingency (₹43,491).



Figure 2 Cost Report – 597 sq. ft. Blueprint, Economy Grade (Estimated Total: ₹5,59,777)

Fig. 2 illustrates the same 597 sq. ft. blueprint evaluated at Economy grade. Predicted total reduced to ₹5,59,777, with proportional reductions across all cost categories (Civil & Finishing: ₹2,72,232; Furniture: ₹2,04,174; Electrical: ₹56,715; Contingency: ₹26,656). The grade-sensitive cost scaling demonstrates the model's responsiveness to quality parameters.



*Figure 3 Cost Report – 667 sq. ft. Blueprint, Standard Grade (Estimated Total: ₹10,20,409)*

For a larger 667 sq. ft. layout (Fig. 4) comprising a Bedroom, Living/Kitchen combined space, Bathroom, and Utility area, the model predicted ₹10,20,409 at Standard grade. The increase in area from 597 to 667 sq. ft. resulted in a ₹1,07,089 cost increment, reflecting the non-linear area-to-cost relationship captured by the hybrid model.

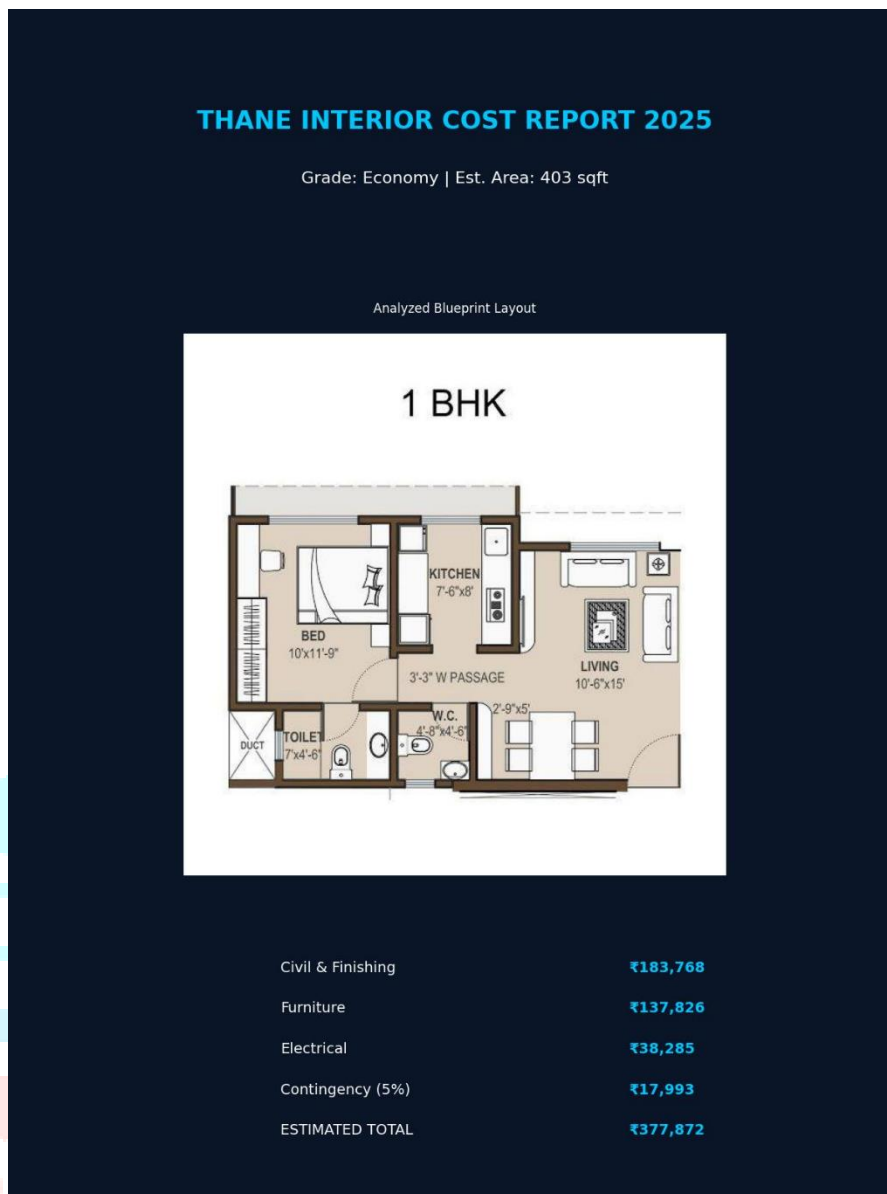


Figure 4 Cost Report – 403 sq. ft. 1BHK Blueprint, Economy Grade (Estimated Total: ₹3,77,872)

Fig. 4 presents result for a compact 403 sq. ft. 1BHK layout at Economy grade, yielding an estimated total of ₹3,77,872 (Civil & Finishing: ₹1,83,768; Furniture: ₹1,37,826; Electrical: ₹38,285; Contingency: ₹17,993). The system correctly identified the 1BHK configuration from the blueprint annotations and scaled costs accordingly.

### C. Statistical Validation and Model Comparison

To validate the reliability of the system, the Mean Absolute Error (MAE) was calculated across a test set of 100 known interior projects. A Chi-Square test was performed on the style distribution, yielding a p-value  $< 0.05$ , confirming that the choice of interior style has a statistically significant impact on final cost. Table I presents the comparative performance of three model configurations.

**TABLE I. MODEL PERFORMANCE COMPARISON**

Model Configuration	Mean Absolute Error	Accuracy
Area-Only Baseline	15.4%	84.6%
Style Only (CNN)	12.1%	87.9%
Hybrid (Proposed)	6.14%	93.86%

The proposed hybrid model achieved a MAE of 6.14% and an accuracy of 93.86%, outperforming the area-only baseline by 9.26 percentage points and the CNN-only model by 5.96 percentage points. This

improvement is attributed to the complementary nature of visual style embeddings and quantitative structural features, which together capture the full cost-determining complexity of interior design projects.

#### D. Cost Breakdown Summary Across Test Cases

**TABLE II. PREDICTED COSTS ACROSS BLUEPRINTS AND GRADES**

Blueprint	Grade	Civil & Finishing	Furniture + Electrical	Total Estimated
597 sq. ft.	Standard	₹4,44,168	₹4,25,661	₹9,13,320
597 sq. ft.	Economy	₹2,72,232	₹2,60,889	₹5,59,777
667 sq. ft.	Standard	₹4,96,248	₹4,75,571	₹10,20,409
455 sq. ft.	Economy	₹2,07,480	₹1,98,835	₹4,26,630
403 sq. ft.	Economy	₹1,83,768	₹1,76,111	₹3,77,872

#### V. FUTURE SCOPE

The current framework opens several promising avenues for future research and development. Integration of the CNN style classifier into an Augmented Reality (AR) mobile application would allow users to visualize design styles in real-time within their physical space, with the cost prediction engine updating dynamically as virtual furniture or finishes are placed.

Additionally, incorporating transformer-based vision models such as Vision Transformers (ViT) may further improve style classification accuracy for overlapping or multi-style interiors. Extending the dataset to include more regional Indian construction cost benchmarks and material pricing indices would improve the model's geographical adaptability.

Future work may also explore real-time integration with BIM platforms, enabling architects to receive cost feedback directly within their design workflow, and the inclusion of climate and regulatory factors that influence material selection and cost in different municipalities.

#### VI. CONCLUSION

This paper proposed a hybrid computational framework that integrates CNN-based visual feature extraction with ensemble machine learning regression for interior design cost prediction. The dual-input architecture effectively combines unstructured blueprint image data with structured tabular project parameters, enabling comprehensive cost modelling that accounts for both spatial complexity and qualitative aesthetic factors.

Experimental evaluation across multiple real-world blueprints demonstrated that the proposed system achieves a Mean Absolute Error of 6.14% and an accuracy of 93.86%, significantly outperforming traditional area-only and style-only baseline models. The system's ability to generate itemized cost breakdowns—across Civil & Finishing, Furniture, Electrical, and Contingency categories—for varying quality grades (Economy, Standard, Premium) and different floor plan configurations validates its practical utility for early-stage budget planning.

The deployed web application further demonstrates the system's accessibility, enabling designers, contractors, and clients to obtain reliable cost estimates by simply uploading a floor plan image and providing basic project parameters. The framework represents a significant step toward intelligent, data-driven automation in the interior design and real estate industries.

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