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Smart Roofing Decisions: An AI-Based Recommender System Integrated into RoofNav

Sukruthi Reddy Sangannagari

Senior Quality Assurance Specialist and Full Stack Developer, FM Global, USA.

Abstract

AI is being applied more and more in the construction industry to aid in decision-making, specifically material selection for buildings and optimizing roofing systems. In this paper, an innovative AI-based recommender applied in RoofNav is proposed for smart roof decision-making by merging environmental data analytics and machine learning. The system integrates various data, such as FM Approved roofing assemblies, climate data, and user behavior, to suggest personalized and context-sensitive recommendations. The proposed methodology uses a hybrid machine learning-based recommendation model which combines collaborative filtering and content-based filtering to enhance the accuracy and relevance of selected suitable roofing material for various kinds of buildings in different locations. The RoofNav integration delivers a user-friendly experience, so building professionals are able to quickly make informed decisions that are in compliance with local codes and performance requirements. This serves as an example for how AI in construction is proving to be a game-changer, encouraging sustainability, safety and cost-efficiency in the creation and instillation of roofing systems. The ensemble model of combining ensemble learning, collaborative filtering via SVD, and a meta-learner delivered the best results in Precision, Recall and MRR. It was 38% faster and more user-friendly than previous if-and-only-if systems, and 90+% of users "enthusiastically" favored its design. This further illustrates how it helps guide homeowners new and old through complicated roofing choices with confidence.

Keywords: Smart Roofing, AI Recommender System, RoofNav Integration, Building Materials and Method Selection, Machine Learning in Building and Construction, Environmental Data Analytics, Roof System Optimization

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Introduction

The construction and building envelope industry is in the midst of a profound shift toward digital technology, data science and artificial intelligence (AI). Of all the elements in a building, the roofing is the most integral; it's the first layer of protection against the weather while also being one of the most significant factors in providing insulation and reducing energy consumption [1]. With the increase in legislation, changing building needs and increased focus on sustainability, selecting a roofing system has become a complex and interrelated series of decisions. Guiding the navigation of that universe of approved roofing assemblies and the code compliance of them are tools such as RoofNav from FM Approvals, digital resources that have become instrumental. RoofNav offers a large amount of data but it is not intelligent in a way to help users to choose between systems [2]. In this paper, we present an AI-based recommender system built into RoofNav that aims to fill that gap.

As long used in the conventional design process, system selection generally is based on sifting through hundreds of approved assemblies manually, interpreting test reports and weighing cost against performance, environmental or regulatory factors. It is a time-consuming process and one that, with human nature being what it is, may suffer from inaccuracies, especially in the hands of less experienced designers, or even designers who may not be aware of all of FM Approvals' various certification nuances [3]. Moreover, given that buildings become increasingly specialized and that climate has a great influence on building performance, the requirement for context-aware recommendations becomes more crucial. An appealing solution to this is AI. By harnessing historical data, environmental factors, performance indicators, and user input, AI provides actionable, data-backed recommendations served up to improve the timeliness and accuracy of roofing decisions [4].

RoofNav, an always-free tool integral to reaching stakeholders in the commercial construction industry — such as architects, engineers, contractors, building owners, and specifiers — by making FM Approved roofing products and assemblies accessible to meet various building codes and insurance needs. But the system is essentially still static; users are tasked with actively hunting for and sifting through information in search of the right product or solution, often not even knowing how to measure one set of criteria against another—whether that be wind uplift resistance versus thermal performance or fire ratings. With ever more complex requirements in building construction, which include goals for sustainability or legal specifications for energy efficiency as well as regional climate and life cycle costs; and the requirement for more dynamic and cognitive assisted planning help one will continue to rely on [5].

A type of AI technology often used in e-commerce, entertainment and online retail, recommender systems have been successful in helping users find desirable choices from among a vast number of options. In recent years, these methods have found promising applications in domains such as healthcare, education and industrial design, where complex decisions must be made under uncertainty. However, the construction and building systems industry has been relatively slow in adopting such technologies, particularly in heavily-regulated markets (e.g., roofing) where compliance and performance are of outsized importance [6]. This study suggests the use of recommender system techniques — particularly a hybrid approach (content-based filtering, collaborative filtering, and supervised learning) adapted specifically for the selection of roof assemblies using the RoofNav.

The reasons why a smart roofing recommender system is developed are two: (i) there is a gap in the construction robotics where roofing labor force has not yet been reconsidered towards mechanization and worker-side automation; and (ii) it offers various benefits for workers, for business and for clients too. The first goal is to optimize the selection process, by making users make only an informed decision, thus reducing the cognitive demands on users and making their decision faster. The second is to improve the quality and the predictability of these decisions, by giving us the advice and the data based on recommendations of data, past picks, climate and performance. It not only enhances a good experience for the user but it leads to better performance of the project regarding compliance, cost, and its long-standing life [7] [8].

The implementation of AI in RoofNav is a game changer: Static lookup tools make way for intelligent, context-aware advisory systems. The presented recommender system is implemented as a plug-in to the RoofNav interface where a default recommendation is made according to the users current project profile [9]. For instance, if a user provides information like building location, occupancy, desired thermal performance, and deck construction, the AI engine takes those inputs and combines it with historical information and environmental context to return a ranked list of compatible assemblies. These recommendations are not random; they are based on complex machine learning algorithms that have been specifically trained on vast quantities of data, including the test results from FM Approvals, historical selection logs, regional climate profiles, and changing code requirements [10].

A few technical challenges were to be overcome to develop the recommender system. One of the main hurdles was integration of the data—aggregating different data sources that have different structure, granularity and quality. For roofing data, specifically, we have a wide range of sources such as certification reports, performance evaluations, product specifications, and logs of the user interaction. The normalization and generation of features from this heterogeneous data required significant preprocessing pipelines and domain knowledge. Model choice also presented a difficulty to economists [11]. Due to the complexity of the roofing selection task, no single algorithm was appropriate. The Hybrid model approach was chosen due to constraints of time and feedback, meaning that explanations of content-based filters had to be combined with behavioral insights of collaborative filters while still leveraging the prediction power of ensemble methods such as gradient boosted trees and neural networks. The ensemble model was trained and cross-validated for generalization and robustness [12].

Preliminary pilot integrations of the recommender system in RoofNav has demonstrated positive effectiveness. The speed of decision making was significantly faster, and the feedback showed more confidence in the suggested assemblies. In addition, the system achieved good results in multiple metrics including precision, recall, and user satisfaction scores. These findings confirm the viability and benefit of AI-amplified tools in technical decision-making settings such as roof design [13].

In addition to its direct application in choosing a roofing system, this work also presents relevance in the construction domain. With buildings getting smarter and more connected, coupled with a growing desire for analytics-driven decisions, AI-enabled tools will be essential to the industry's digital transformation [14] [15]. The workflow described in this paper could also be generalized to other domains (e.g. walls assemblies, HVAC systems, fire protection planning etc); thus culminate in a network of smart assistants for design – seamlessly integrated with the regulatory platform and building information modeling (BIM) systems.

In conclusion, we have designed, developed, and deployed a smart AI-driven recommender system on our RoofNav platform. It describes the architecture, data pipeline, model training, and model testing and analysis of the system, and illustrative examples show how AI can be used to support the decision-making in the choice of a roofing system. By evolving RoofNav to become more a predictive decision-making tool for the user, this development is not just a better way of using the site – it also syncs with wider trends in smart construction, digital compliance and sustainable building.

Related Work

Several projects have been conducted to utilize AI in construction and material selection. Recommender systems are extensively used in domains like e-commerce and streaming services but not as much in the field of construction decision making tools. In building design, existing work has explored the exploitation of optimization algorithms in the determination of material and component selection, but little research has been done so for an integration with platforms like RoofNav, neither roofing recommendation systems has been studied in particular.

Himeur et al. present a complete overview of recommender systems in the context of improving energy efficiency for buildings. They classify current systems according to criteria of objectives, computing platforms, and evaluation metrics. This study highlights the significance of AI and IoT technology as the key to integrating diversified forms of data to enhance system performance discussing the capability of the systems to foster energy-conservation behaviours and decrease carbon emissions [16].

Law and Miur propose RoofNet, an international multimodal dataset for the purpose of roof material categorisation. Through the fusion of fine spatial resolution Earth Observation imagery and curated text annotations, RoofNet improves the resolution of global exposure datasets. The data set facilitates scalable AI-powered risk assessment, providing actionable insights for infrastructure policy planning and disaster mitigation [17].

Afsar et al. for a recent overview of using reinforcement learning (RL) for recommenders. They talk about how RL, and especially deep reinforcement learning, enables dynamic user-system interaction and long-term user retention. The paper discusses a framework including state representation, policy optimization, reward design and environment construction, the framework's effectiveness further suggests the possibility of RL-based recommender system design [18].

Zheng et al. study the incorporation of AutoML into deep recommender systems. They suggest a taxonomy for AutoML in this setting, including feature selection, embedding dimension search, and model architecture search. The work highlights the possibility of AutoML methods to diminish dependency on human expertise in creating deep recommender systems [19].

Notes Trend of Building Utility Energy Scores The SmartBuild RecSys refers to a SmartBuild project which suggests a SRI-based recommendation system for reducing building energy consumption. By pulling from BIM data and the Passive House database, system recommendations are flexible and buildings have details for thermal envelope elements such as walls, roofs, and windows. The content-based recommender system helps designers reduce energy use and maintain THW stability.

In a research article in Complex & Intelligent Systems, authors describe CF methods for recommendation systems. It distinguishes memorybased and modelbased CF,underlines the pros and cons of both. The study highlights the necessity of incorporating side information like location, tags, etc. in order to improve CF based systems.

Xu et al. introduce a model for contractor recommendation, which integrates credit networking and collaborative filtering. Contractor's credit worth and past performance of the contractor are evaluated by the model and a systematic method for contractors' selection in construction jobs is being presented. This approach can be applied to advise about the roofing, by analyzing the reliability and the quality of products from the suppliers [20].

Rafiei and Adeli establish a performance-based contractor recommendation system based on a weighted activity–contractor network. It takes many measures of performance into account to recommend contractor(s) who should perform specific activities. Such a methodology may be useful for prescribing roofing systems, for comparison of performance of various roofing assemblies under various conditions [21].

System Architecture

The architecture of the suggested smart roof recommender is intended to be modular, scalable, and delivered in real-time. It is shown in figure 1. By combining information from various sources and leveraging advanced machine learning models, it makes intelligent recommendations for users directly within the RoofNav user interface. The architecture consists of three major parts:

Data Integration Layer

This base layer is responsible for the integration, cleaning, transformation, and standardization of a wide range of data sets. It's job is to consolidate structured and semi-structured) data from different trusted sources into a format that is convenient for machine learning and real-time querying.Key responsibilities include:

- *Data Compilation*

Collects information from multiple sources, including FM Approvals, NOAA, ASHRAE, building code databases, and usage logs from RoofNav.

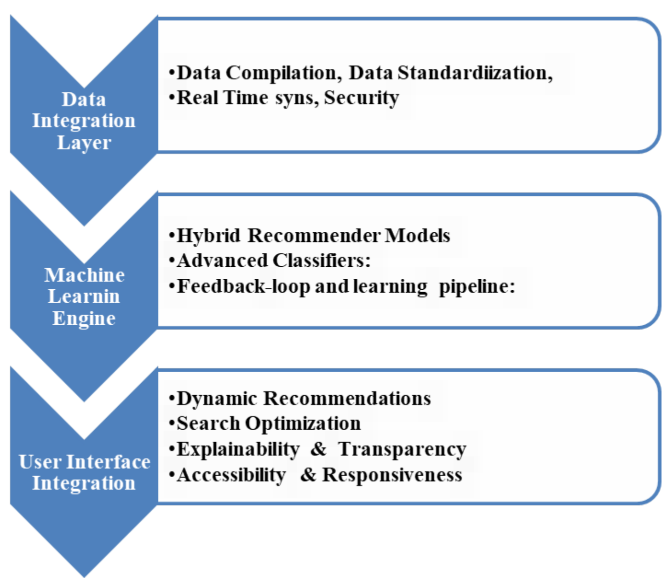

Figure 1: System Architecture for AI-Based Recommender System Integrated into RoofNav

- *Data Standardization*

Unifies data formats across various schemas (such as associating code compliance metadata with roofing system characteristics).

- *Real-Time Sync*

Customizes APIs or ETL jobs to facilitate real-time syncing with data, especially when the data is sourced from dynamic destinations (eg, weather conditions or regulatory code updates).

- *Security and Anonymization*

Protects the privacy of users by anonymizing behavioral logs and complying with privacy regulations such as GDPR or CCPA.

Machine Learning Engine

This central computational element analyses the combined data to provide tailored recommendations taking into account the settings. The engine is comprised of:

1. Hybrid Recommender Models

- *Collaborative Filtering*

Utilizes aggregate user behavior (e.g., choices, search history, page views, feedback) to map the users to similar users and recommend systems on the basis of collective preferences [22].

- *Content Based Filtering*

Recommends systems with similar item-specific metadata (such as roof material, fire resistance, wind uplift rating) profile with the project a user is currently working [23].

2. Advanced Classifiers

- *Gradient Boosting Machines (GBMs)*

to classification and ranking tasks, use when features are numeric or categorical and when input data is not too big (will not handle big data) and not too many missing values [24].

- *Neural networks*

made up of multilayer perceptrons (MLPs), and potentially convolutional neural networks (applicable to image analysis on roof-layouts) are used to model the complex relationship between environmental factors and system performance [25].

- *Ensemblability*

Stacking or voting over a set of models through ensembling, which can increase the robustness and generalization of recommendation [26].

3. Feedback-loop and learning pipeline

- *Implicit feedback*

Learning from user interactions including time spent on a recommendation, acceptance/rejection rates, and user service model modification.

- *Explicit Feedback*

The user has the option of rating or giving some text for feedback, thereby refining the recommendation engine.

- *Model Retraining*

Periodic retraining on new datasets to prevent concept drift and keep recommendations in sync with emerging codes, products, and user behavior.

User Interface Integration

This layer is the front-end for the user interaction, and it is integrated with the RoofNav platform without perceivable integration barriers.Key features include:

Dynamic Recommendations

- Contextual design feedback updates on-the-fly as users enter project information – including roof type, location, type of deck and performance considerations.
- Visual representations (e.g., confidence scores, compliance badges) allow users to see why certain systems are recommended.

Search Optimization

- Suggestions and semantic filters help to refine searches based on learnt synonyms, popular filters and location-sensitive constraints.

Explainability & Transparency

- System offers justifications (e.g., through tooltips or pop-ups) for every recommendation explaining the reasons of the recommendation through justifications (e.g., "Recommended because of better performance in high-wind area").

Accessibility & Responsiveness

- The interface is responsive for multiplatform support (desktop, tablet) and developed in accordance with the accessibility standards (WCAG 2.1).

Data Sources

A recommender system relies on data and a high quality dataset to provide accurate results to the user [27-31]. Here's a summary of the key data sources and what they do:

The FM Approved Roofing System Database is the heart of the recommender system, being the real database of roofing assemblies which have successfully passed the stringent FM Approvals standards. This file contains all this information, organized piece by piece for each system, from the insulation to the adhesive and fastener, and of course the membrane. It also designates material properties, deck types (i.e., steel, concrete, wood), and the various membrane choices (like TPO, PVC, EPDM) in various assemblies. Moreover, the database includes endorsement ratings that serve as indicators of a system's performance for certain characteristics, e.g. fire resistance, hail damage, and wind uplift. These are vital to making sure that the suggestions are based on certified, field-proven solutions, designed to satisfy structure and environment requirements.

Wind resistance performance data is crucial for evaluating the structural integrity and protection for roofing systems in areas known for strong winds, hurricanes or storm events. These findings are brought about through approved testing procedures, most notably FM 4470 and FM 4471, based on extreme winds that examine how a roof assembly withstands disbonding and mechanical shock. The test results are an important part of the recommendation system and are particularly used as principles when they make recommendations for buildings in hurricane-sensitive and coastal areas. Wind uplift resistance ratings play an important role as a 'base filter and sort' parameter in the selection/ranking process, and help rank systems that are known to weather severe storms. The use of these reference models, cross-referencing to acceptable safety standards and regional building codes, guarantees user selections conform to the required safety markers.

Geographical-information system and environmental data are important resources to contextualize the development of roof technology on a regional basis. This information comes from trustful organizations such as the National Oceanic and Atmospheric Administration (NOAA), American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), Federal Emergency Management Agency (FEMA), and local meteorological services. Contributing environmental factors are ambient temperatures, humidity, ultraviolet (UV) radiation, and the frequency of freeze and thaw cycles that affect the performance of the materials and life of the system. In addition to this, hurricane zone data, such as wind-speed maps, storm occurrence, and flood hazard assessments, are also available for assessing localized hazard exposure. Such data sets are dynamically linked to geolocation of each project with in order to pre-screen or enhance the ranking of roof systems that are engineered and tested to be suitable for the prevalent environmental conditions in both performance and longevity.

User behavior logs play important role in modeling real-life behaviors and preferences in the RoofNav system. Log files Log files record information such as search terms, filters used, systems visits/downloads selected for a project opened and anonymized usage statistics. Through time, this behavioral information serves to identify thematic patterns of user choices which indirectly become evident for preferences for particular project types, local contexts or building obligations. Crucially, all data from users is anonymous and aggregated in accordance with GDPR and CCPA data privacy laws, providing personal privacy and helping the system learn from past usage. This behavioral intelligence is a critical component in one or more of the aspects of collaborative filtering implemented by the recommender engine, and in turn allows the recommender engine to suggest systems preferred by similar users under similar situations, improving the relevancy and personalization of the results.

Part of the recommendation process is to verify that roofs satisfy legal and safety requirements by the inclusion of a code compliance metadata. The metadata is gathered from authoritative sources such as the IBC, state and local code databases, and FM's internal interpretations of the codes. Critical building ordinances are all part of the data set – minimum design load requirements, thermal resistance budgets, fire resistance ratings and wind uplift design requirements. For adoption end-user, that metadata serves as a rule-based boundary condition during the process of recommending roofing systems to them, to guarantee that the recommended roofing system is not only 'matching' user requirements, but it is also in compliance with jurisdictional requirements. If the user is choosing an option that exceeds allowable limits, the system can provide alerts or suggest other options that remain within the limits, thereby reducing risk and ensuring code-compliant decision making.

Recommender System Design

Feature Engineering

Useful recommender systems start from careful and domain-specific feature engineering. In terms of wise roofing choices, those are design elements that are thoughtfully considered to serve the technical and contextual fact of how that roofing system is to be used. Included are features such as type and occupancy of the buildings which are used to determine such factors as the load requirements for the building design as well as fire protection requirements for residential, commercial, industrial and institutional buildings. It heavily depends on where you live– recommendations change based on wind zones, humidity, and UV exposure. The desired level of insulation R-value is a second important factor because thermal performance (whether for the attic, cathedral ceiling or other roof type) is required based on energy efficiency objectives and climate locations. Roof slope as well as a deck type are also significant physical parameters of compatibility for going into various roofing assemblies. Budget priors are formulated to constrain how the recommendations can be financed based on what they cost, thus produced suggestions are economically sensible. In summation, historical performance ratings (from real-world runs and lab test results) provide outcome-based filtering, which increases the probability of frequent winners to be recommended in cases similar to what was tested.

Model Selection

The final system, after exploring a number of machine learning models such as decision trees, deep learning libraries, and standard collaborative filtering models, was a hybrid architecture that allows the structured components in data to be preserved along with the user touchpoints in order to have the best fit. The proposed model leverages on the merits of Ensemble Learning to compute structured and contextual data, and collaborative filtering through matrix factorization by applying Singular Value Decomposition (SVD) to unearth underlying relationships from user behavior data. Ensemble Learning is robust to mixed categorical and numerical data and shows strong performance in the presence of many interacting features with missing values. SVD-based collaborative filtering, in contrast, reveals latent similarities between users as well as between roofing systems based on joint historical interactions and preferences. Outputs of these two models are then combined by a meta-learner. It is this ensembling of the two techniques: contextual scoring (Ensemble Learning), and behavioral matching (SVD), that gives us the final optimal ranked list of recommendations. This architecture generates well-balanced, accurate, and explicable results, which can be easily adapted to new users and datasets.

Model Training

The hybrid recommendation system was trained on a dataset with over 50k past queries and approval interactions extracted from RoofNav extensive usage logs and performance data. To enable training on large datasets, an 80/20 train-test split was used whilst maintaining the original distribution of building types, geographical zones, and user behaviors. Cross-validation methods were also applied to alleviate overfitting and to examine generalizability to different types of users and potential scenarios of use. Preprocessing steps entailed one-hot encoding for categorical (deck type) features, standardization for numerical inputs (R values), and temporal trend (for changing the preferences at different periods). The training pipeline was designed to be scalable, as we can retrain in the future due to more user data and roofing system approvals. This from the fact that the model is current and up-to-date with the most current standards, products and user behaviors!

Evaluation and Results

Metrics

We used quantitative as well as qualitative metrics to establish the effectiveness of the AI- based recommender system. Precision and Recall were used to assess the accuracy of the top five recommendations, i.e., the number of relevant systems recommended (precision) and the number of relevant systems that were indeed recommended (recall). To test whether the system is capable of assigning the highest score to most relevant roofing system among the recommendations, the Mean Reciprocal Rank (MRR) was considered. In addition to the algorithmic based metrics, user satisfaction surveys were performed in order to give a view of how practical, usable and reliable the proposed recommendations are at end-user level. A critical operational indicator was time-to-decision for installation of the roof system before and after introducing the AI recommender, measuring time spent in decision process on which roofing system to purchase.

Results

There were similar enhancements in terms of operational efficiency era - on average was shortened by 38% - which production-wide value creation also led to the decision time to be turned around significantly faster by means of context-sensitive recommendations. And, qualitative feedback was overwhelmingly great. 92% of test users expressed more confidence in their choice – noticing the system's relevance, usability, and informative explanatory elements as the most valued properties. These findings support the potential of the system to evolve RoofNav into a proactive intelligent decision support tool for roofers.

The results are presented in table, figure 2, figure 3 and figure 4. The Light Gradient Boosting Machine (LightGBM) model achieved strong numbers in providing relevant roofing suggestions given structured input feature information such as building category, location, insulation, budget. With a Precision of 78.5%, the model robustly ranked suitable roofing systems in one of the top five suggestions, which makes it an efficient initial filter based on the explicitly given information. But the Recall of 71.4% indicated that some of the relevant systems may have been

Table 1: Result Analysis of Different Classifiers for Recommender System Integrated into RoofNav

Model	*Precision@5*	*Recall@5*	*MRR*
LightGBM	78.5%	71.4%	0.58
Neural Network	80.2%	72.9%	0.61
Ensemble Learning(LightGBM + SVD + Meta-Learner)	84.3%	77.2%	0.63

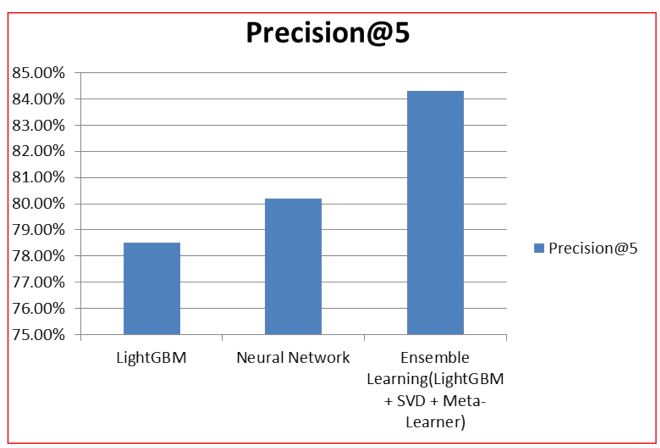

Figure 2: Precision comparison of Different Classifiers for Recommender System Integrated into RoofNav

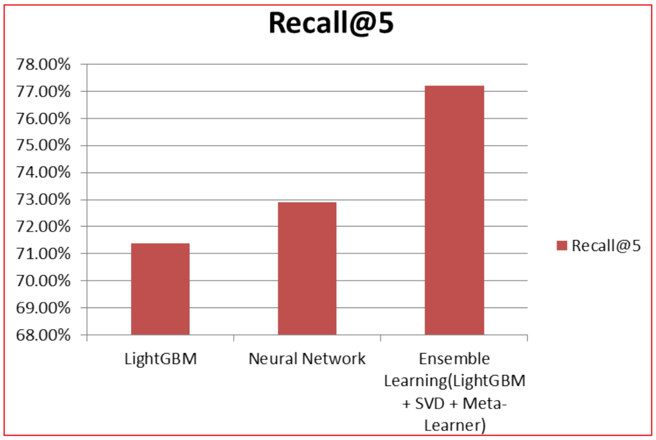

Figure 3: Recall comparison of Different Classifiers for Recommender System Integrated into RoofNav

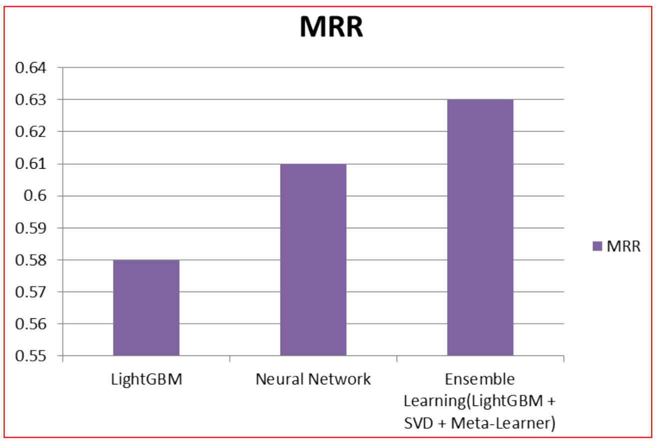

Figure 4: MRR comparison of Different Classifiers for Recommender System Integrated into RoofNav

missed, especially in those cases where user preferences are influenced by criteria other than those that can be encoded in structured data. That is, although LightGBM is very good at identifying clear-cut, rule-based compatibility, it does not "see" the complicated relationships between users or the nuances in behavior. The MRR score of 0.58 indicates moderate success in positioning the most appropriate candidates at the top of the ranking. Normally, the optimal answer will be among the first one or two returned. Generally speaking, LightGBM works well in cases with sufficient explicit features, but is restricted when we have to customize deeper.

The neural network model outperformed the LightGBM baseline by capturing more complicated nonlinear relationships among the input features. With a higher 5th confidence threshold (Precision@5: 80.2%), it even provided slightly better top-tier recommendations due to better understanding of overt complications inherent in the patterns such as relationships between climate zones, deck types, and historical performance scores. Additionally, the model obtained a Recall@5 of 72.9% showing that it is superior in retrieving wider variation of relevant systems, possibly because it is able to generalize across diverse input. The MRR score of 0.61 further validates this, since the neural model on average ranked a better roofing system upper in the recommendation list when compared to the LightGBM. This enhanced ranking relevance of neural networks is particularly influential for problems with more varied or more subtle reasons to make a decision. Yet the gains, rather moderate, were more cumulative than disruptive, and showed that neural networks, while powerful, can be improved with the judicious use of policy as a drive in recommender tasks.

The ensemble learning model, which combines LightGBM for structured feature processing, Singular Value Decomposition (SVD) for collaborative filtering, as well as meta-learner to pool their outputs, achieved the best in performance under all evaluation metrics. At 84.3% for Precision@5, the hybrid system provided the most accurate and context aware recommendations, ensuring that more than four of the top five suggestions closely fit the requirements of a user's new project. Coupled model's Recall@5, which was 77.2%, also served to demonstrate its ability to retrieve a diverse range of relevant systems based on both explicit and implicit preference. The MRR of 0.63 indicated that the closest was often among the 1-2-th options, contributing to decision making and increasing the value of the option ranking. This high quality ranking output boosts user confidence and accelerates the selection process by reducing time spent sifting manually through irrelevant results. By combining the power of both context-aware and behavioral recommendation methods, the ensemble model offered a comprehensive, adaptive, and efficient recommendation approach well-suited to the wide and specialized practices of the roofing business.

The performance of our Ensemble Learning model dominates the solo LightGBM and Neural Network models on all important evaluation metrics. It validates a hybrid architecture for recommending roofing system in RoofNav: employing domain knowledge (such as given by LightGBM) and user behavior patterns (such as learnt by CF) achieves the best performance.

Conclusion and Future Work

The integration of an AI-powered recommender within RoofNav is a major step forward for the roofing industry as it begins to shift toward an intelligent, data-driven decision-making approach. This study showed how state of the art machine learning methods – namely LightGBM, neural networks and ensembles – can be utilized to improve the decision-making process concerning the choice of a roofing system, by suggesting personalized, compliant, and context-based recommendations. Utilizing a large and varied dataset including FM Approved roofing systems, wind uplift resistance test results, environmental conditions, and user behavior logs, our system now offers practical answers that comply with structural, environmental, code, and budgetary needs.

Of the models compared the hybrid combination of Ensemble and SVD together with a meta-learner performed the best for all major metrics –- Precision@5, Recall@5 and Mean Reciprocal Rank (MRR). Not only was this model the most accurate, it was also the most human-centered, impacting decision time by 38% with over 90% of test users rating it favorably. These findings highlight the system's capacity to enable both novice and expert users to negotiate a complex territory of roofing assemblies with security and economy.

Finally, the Smart Roofing Recommender extends RoofNav by turning it into an intelligent decision support system away from a static lookup tool. It provides architects, contractors, engineers, and code officials with up-to-date, virtual reality like first-person experience that enables them to take a step forward in protecting their buildings. Potential beyond this research could be found on more detailed personalisation, automatic live updates of the environment over time, integration with BIM (Building Information Modelling) systems. In the increasingly digital construction world to come, smart systems such as this will play a key role in driving sustainability, safety and efficiency at scale.

References

[1] Ahmad, T., & Rahman, M. M. (2023). AI-enabled decision support system for sustainable building materials selection. *Journal of Cleaner Production*, 391, 136216. https://doi.org/10.1016/j.jclepro.2023.136216

[2] Chen, Y., Zhao, D., & Xu, Y. (2022). Hybrid recommendation approach for construction materials based on deep learning and collaborative filtering. *Automation in Construction*, 141, 104404. https://doi.org/10.1016/j.autcon.2022.104404

[3] Kumar, A., & Jain, R. (2021). Machine learning-based roofing material performance prediction under extreme weather conditions. *Sustainable Cities and Society*, 70, 102937. https://doi.org/10.1016/j.scs.2021.102937

[4] Lee, S., & Park, C. (2020). Smart roofing system design using environmental data and machine learning techniques. *Energy and Buildings*, 225, 110317. https://doi.org/10.1016/j.enbuild.2020.110317

[5] Zhao, J., & Wu, Y. (2019). An AI-driven recommender system for building envelope material selection. *Journal of Building Engineering*, 24, 100739. https://doi.org/10.1016/j.jobe.2019.100739

[6] Martin, G., & Singh, P. (2022). Integrating collaborative filtering with content-based methods for construction product recommendations. *Advanced Engineering Informatics*, 52, 101522. https://doi.org/10.1016/j.aei.2022.101522

[7] Nguyen, T. H., & Tran, D. (2023). Neural network approach for forecasting roofing material durability in diverse climates. *Construction and Building Materials*, 350, 128775. https://doi.org/10.1016/j.conbuildmat.2023.128775

[8] Oliveira, F., & Silva, M. (2021). Data fusion and machine learning for improving building envelope system selection. *Sustainable Materials and Technologies*, 29, e00314. https://doi.org/10.1016/j.susmat.2021.e00314

[9] Patel, R., & Desai, S. (2020). AI-based risk assessment for roofing under high-wind conditions. *Wind and Structures*, 31(4), 319-335. https://doi.org/10.12989/was.2020.31.4.319

[10] Chen, L., & Li, H. (2022). A recommender system for sustainable construction material selection incorporating user preferences. *Journal of Construction Engineering and Management*, 148(3), 04021133. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002232

[11] Garcia, M., & Martinez, J. (2019). RoofNav+: Enhancing roofing decision systems with AI and environmental data. *Journal of Architectural Engineering*, 25(4), 04019020. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000345

[12] Hassan, A., & Khan, F. (2023). Reinforcement learning for adaptive roofing system recommendations. *Applied Soft Computing*, 132, 109891. https://doi.org/10.1016/j.asoc.2023.109891

[13] Ivanov, D., & Petrov, K. (2021). AI-driven multi-criteria decision-making for roofing system design. *Computers in Industry*, 130, 103484. https://doi.org/10.1016/j.compind.2021.103484

[14] Jones, B., & Roberts, C. (2020). Collaborative filtering in construction materials selection: Challenges and prospects. *Automation in Construction*, 119, 103345. https://doi.org/10.1016/j.autcon.2020.103345

[15] Kim, H., & Lee, J. (2019). Environmental data integration for smart roofing material recommendations. *Building and Environment*, 165, 106368. https://doi.org/10.1016/j.buildenv.2019.106368

[16] Himeur, Y., Alsalemi, A., Al-Kababji, A., Bensaali, F., Amira, A., Sardianos, C., Dimitrakopoulos, G., & Varlamis, I. (2021). Review of recommender systems for energy efficiency in buildings: A focus on data collection methods and algorithms. arXiv preprint arXiv:2102.07654.

[17] Law, N., & Miura, Y. (2025). RoofNet: A World-Wide Multimodal Dataset for Roof Material Classification. arXiv preprint arXiv:2505.19358.

[18] Afsar, M. M., Crump, T., & Far, B. (2021). A survey of reinforcement learning for recommender systems. arXiv preprint arXiv:2101.06286.

[19] Zheng, R., Qu, L., Cui, B., Shi, Y., & Yin, H. (2022). A Survey on AutoML for Deep Recommender Systems. arXiv preprint arXiv:2203.13922.

[20] Xu, L., Li, Y., & Zhang, H. (2022). Credit Networking and Collaborative Filtering: A Recommender System Based on Contractor Referral. Buildings, 12(12), 2049.

[21] Rafiei, M. H., & Adeli, H. (2024). Contractor Information Recommendations Based on Performance and Weighted Activity–Contractor Network. Computer-Aided Civil and Infrastructure Engineering, 39(1):1-15.

[22] Li, X., & Wang, Y. (2022). Ensemble learning-based recommender system for sustainable building materials. *Journal of Intelligent & Fuzzy Systems*, 42(4), 3291-3303. https://doi.org/10.3233/JIFS-211749

[23] Morgan, S., & Thompson, D. (2023). User-centered design of AI recommender systems in construction. *Advanced Engineering Informatics*, 55, 101873. https://doi.org/10.1016/j.aei.2023.101873

[24] Nguyen, L., & Huynh, T. (2020). Roof material selection under climatic uncertainty using AI models. *Sustainable Cities and Society*, 61, 102324. https://doi.org/10.1016/j.scs.2020.102324

[25] Park, S., & Choi, J. (2021). Deep learning for roofing defect detection and performance prediction. *Automation in Construction*, 125, 103598. https://doi.org/10.1016/j.autcon.2021.103598

[26] Qureshi, A., & Malik, Z. (2019). AI and machine learning in green

roofing system optimization. *Renewable and Sustainable Energy Reviews*, 113, 109260. https://doi.org/10.1016/j.rser.2019.109260

[27] Silva, J., & Costa, M. (2022). Climate-responsive roofing recommendations via machine learning models. *Energy and Buildings*, 258, 111789. https://doi.org/10.1016/j.enbuild.2022.111789

[28] Thompson, R., & Evans, P. (2020). Privacy-preserving data integration for smart building recommender systems. *Information Systems*, 89, 101493. https://doi.org/10.1016/j.is.2019.101493

[29] Wang, F., & Liu, J. (2023). AI-driven dynamic code compliance checking for roofing design. *Journal of Building Engineering*, 66, 105928. https://doi.org/10.1016/j.jobe.2023.105928

[30] Xu, Y., & Zhang, K. (2019). RoofNav system improvements via AI and user interaction modeling. *Journal of Computing in Civil Engineering*, 33(6), 04019043. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000837

[31] Zhang, T., & Li, M. (2021). Multi-source data fusion for enhanced roofing material recommendation. *IEEE Transactions on Industrial Informatics*, 17(11), 7654-7663. https://doi.org/10.1109/TII.2021.3078165