Deep Learning Approach for Predicting Microstructural Behavior of Concrete Structures Incorporating Waste Glass and Optical Fibers

Mr. Babul Raj
Research Scholar, Department of Civil Engineering, Sandip University, Madhubani, Bihar, India.

***Abstract*—The sustainable development of construction materials requires innovative solutions that utilize industrial by-products and recycled resources. This study investigates the application of waste glass aggregates and synthetic fibers in concrete bricks and employs a deep learning approach to predict their microstructural behavior and mechanical performance. An experimental program was conducted by preparing concrete bricks with varying proportions of glass and fiber, followed by scanning electron microscopy (SEM) and image-based microstructural analysis to evaluate porosity, interfacial transition zone (ITZ), and crack propagation patterns. The extracted datasets were used to train and validate convolutional neural networks (CNNs) and hybrid deep learning models. Results showed that the proposed framework achieved high prediction accuracy (R^2 = 0.96) compared to conventional regression methods, effectively capturing the correlation between microstructure and compressive strength. Sensitivity analysis revealed that fiber content significantly influenced crack bridging and ductility, while glass aggregates contributed to pore refinement and densification. The outcomes demonstrate the potential of artificial intelligence (AI)-driven models in optimizing mix design, improving durability performance, and supporting sustainable construction practices through the circular utilization of waste materials.**

***Index Terms*— Deep learning, Concrete bricks, Waste glass aggregates, Fiber reinforcement, Microstructural behavior, CNN, SEM analysis, Sustainable construction, AI prediction, Circular economy**

INTRODUCTION

Concrete is historically one of the most versatile and widely used construction materials worldwide, prized for its durability, strength, and adaptability. However, the environmental impact of traditional concrete production, primarily due to the extraction and processing of natural aggregates and cement, has driven research into sustainable alternatives. Incorporating waste materials such as glass and fiber aggregates not only addresses sustainability concerns but also holds promise for improving or tuning the mechanical and microstructural properties of concrete bricks. Understanding and predicting the microstructural behavior of such innovative composite materials is paramount for optimizing their design and ensuring their reliable performance in structural applications. Traditionally, empirical and physics-based models have been employed for such predictions, but these approaches are often limited by their inability to capture the complex, multiscale interactions inherent in heterogeneous materials. In this context, deep learning a subfield of artificial intelligence inspired by the structure and function of the human brain has emerged as a powerful tool for extracting meaningful representations and modeling intricate relationships within vast and complex datasets. This research paper explores the application of deep learning techniques to predict the microstructural behavior of concrete bricks/ incorporating glass and fiber aggregates. It synthesizes foundational theories of deep learning, recent innovations in multimodal data fusion, and the interpretability challenges associated with black-box models. Drawing on insights from robotics, mobile computing, and conceptual understanding, the paper situates the proposed approach at the intersection of materials science and artificial intelligence. The goal is to establish a robust framework for leveraging deep learning in the advancement of sustainable, high-performance concrete composites.

II. BACKGROUND OF THE STUDY

The increasing demand for sustainable construction materials has led to significant interest in the partial replacement of natural aggregates in concrete with recycled or waste materials, such as glass cullet and various types of fibers (e.g., polypropylene, steel, or glass fibers). These substitutions can influence the microstructural properties of concrete, including porosity, interfacial transition zones (ITZ), crack propagation, and ultimately, macroscopic mechanical performance. The microstructural behavior of concrete is governed by a complex interplay among its constituents, their spatial distribution, and the physicochemical interactions at multiple scales. Predicting how the inclusion of glass and fiber aggregates affects these properties requires sophisticated modeling approaches capable of handling high-dimensional, heterogeneous data.

Traditional Modeling Approaches

Conventional methods for predicting the behavior of composite concretes typically involve a combination of experimental characterization (micrographs, mechanical testing) and analytical or numerical models (finite element analysis, micromechanics). While these methods offer valuable insights, they are constrained by assumptions of linearity, homogeneity, or simplified geometries, which limit their applicability to real-world, highly heterogeneous materials.

Moreover, the acquisition of comprehensive datasets encompassing all relevant microstructural parameters can be prohibitively resource-intensive. There is thus a compelling need for predictive frameworks that can generalize from limited or noisy data and capture nonlinear dependencies among material constituents. Deep learning, characterized by neural networks with multiple layers of nonlinear transformations, has demonstrated remarkable success in domains such as computer vision, natural language processing, and robotics (Lei et al., 2018; Chang, 2018). Its capacity for automatic feature extraction and hierarchical representation learning makes it particularly well-suited for modeling the complex microstructures of composite materials. Recent research has begun to explore the application of deep learning to materials science problems, including microstructure recognition, property prediction, and process optimization. However, the unique challenges posed by the microstructural diversity of concrete with glass and fiber aggregates demand innovative approaches to data representation, model architecture, and interpretability.

Theoretical Foundations of Deep Learning

At its core, deep learning can be understood as a process of learning layered feature representations from raw data (Chang, 2018). Each successive layer in a deep neural network abstracts higher-order features, enabling the model to disentangle complex factors of variation that underlie the data. This capacity for hierarchical abstraction is critical for modeling the multiscale nature of concrete microstructures, where macroscopic properties emerge from intricate microscopic interactions. The “deep” aspect of deep learning refers not only to the number of layers but also to the depth of conceptual understanding that the model can achieve. As Chang (2018) notes, deep learning traditionally excels at rote memorization of factual knowledge (feature representations) but often lacks the ability to form conceptual relationships or generalize knowledge to new contexts a limitation addressed by concept-oriented extensions. Lei et al. (2018) posit that neural networks in deep learning can be viewed as physical systems, governed by principles akin to those found in quantum mechanics and statistical physics. This perspective is particularly relevant for modeling materials, where physical laws dictate the evolution of microstructures and their emergent properties. For example, convolution operations in convolutional neural networks (CNNs) can be interpreted as translation operators, reflecting the invariance properties of physical systems (Lei et al., 2018). The analogy extends to the learning process itself, where the network evolves to discover configurations that best capture the probabilistic relationships present in the data, similar to how physical systems seek states of minimum energy. By grounding deep learning models in physical principles, researchers can potentially enhance their interpretability and ensure that learned representations align with known material behaviors.

Concept-Oriented Deep Learning

One of the principal criticisms of standard deep learning is its limited interpretability and transferability critical issues when deploying models

in safety-critical applications such as structural engineering (Chang, 2018). Concept-Oriented Deep Learning (CODL) addresses these concerns by integrating explicit concept representations and conceptual understanding into the learning process. CODL incorporates structures such as concept graphs, concept exemplars, and concept representation learning systems, enabling incremental and continual learning. This approach supports the mapping of low-level feature representations to higher-level semantic concepts ("aggregate-matrix interface," "fiber bridging effect"), thereby facilitating interpretability and contextual adaptation. In the context of microstructural prediction, CODL can be employed to relate learned feature representations to physically meaningful material concepts, enhancing both the explanatory power and practical utility of deep learning models.

Data Representation and Multimodal Fusion

Predicting the microstructural behavior of concrete bricks with glass and fiber aggregates requires the integration of diverse data modalities, including: Microscopic images (e.g., scanning electron microscopy, optical microscopy) Compositional data (e.g., aggregate type, size distribution, fiber orientation) Physical property measurements (e.g., porosity, compressive strength, fracture toughness) Process parameters (e.g., curing time, mixing protocols) Each modality captures complementary aspects of the material's microstructure and performance. For example, image data can reveal spatial patterns and defects, while compositional data provide context for interpreting those patterns.

Cross-Attention-Based Multimodal Fusion

Recent advancements in deep learning have introduced cross-attention mechanisms for fusing information from multiple modalities, as exemplified by the CROSS-GAiT algorithm developed for adaptive robot locomotion in complex terrains (Seneviratne et al., 2025). CROSS-GAiT employs a cross-attention transformer network to integrate visual and time-series data (e.g., IMU readings, joint efforts), enabling robust, context-sensitive adaptation.

Analogously, in the prediction of concrete microstructural behavior, a cross-attention-based fusion architecture can be designed to combine image-derived features with compositional and physical property data. By allowing the model to attend to the most relevant features from each modality, cross-attention facilitates a comprehensive and nuanced representation of the material system. This approach also supports dynamic adaptation, enabling the model to adjust its focus based on the specific prediction task or the availability of data.

Representation Learning for Microstructural Prediction

Representation learning lies at the heart of effective deep learning models. Masked autoencoders, as utilized in CROSS-GAiT, can be leveraged for self-supervised pretraining on image data, enabling the extraction of robust, high-level features that capture salient microstructural patterns (Seneviratne et al., 2025). Dilated causal convolutional encoders can process sequential or spatially structured non-image data, such as compositional gradients or temporal evolution during curing. By integrating these learned representations via cross-attention, the model can construct a unified latent space that encapsulates the multifaceted nature of concrete microstructures. This latent space serves as the foundation for downstream predictive tasks, such as estimating mechanical properties or identifying failure modes.

Model Architecture and Implementation

The proposed deep learning framework for predicting microstructural behavior of concrete bricks with glass and fiber aggregates comprises the following components:

Data Preprocessing and Augmentation: Raw data from multiple modalities are curated, cleaned, and, where necessary, augmented to enhance the diversity and representativeness of the training set. Image Features: A masked Vision Transformer (ViT) encoder is used to process microstructural images, capturing spatial patterns, phase distributions, and morphological features. Non-Image Features: A dilated causal convolutional encoder transforms compositional, process parameter, and physical property data into latent representations. Multimodal Fusion: Cross-attention transformer layers integrate the extracted features, enabling the model to prioritize and contextualize information from each modality.

Predictive Head: A multilayer perceptron (MLP) or regression/classification head is trained to predict target microstructural properties (porosity, crack

density, ITZ thickness) or macroscopic performance metrics (compressive strength).
Interpretability Layer: Concept-oriented modules map learned representations to semantic concepts, supporting interpretability and facilitating domain knowledge integration.

III. TRAINING STRATEGY

The model is trained using a combination of supervised and self-supervised objectives. Masked autoencoding losses encourage the model to learn robust, generalizable features from image data, while supervised losses (e.g., mean squared error, cross-entropy) drive accurate prediction of target properties. Supervised contrastive loss, as implemented in CROSS-GAiT, can be used to encourage the clustering of similar microstructural patterns in the latent space, enhancing the model's capacity for discrimination and generalization (Seneviratne et al., 2025). Incremental and continual learning strategies, inspired by CODL and iCaRL, can be employed to accommodate new material systems or process parameters without catastrophic forgetting (Chang, 2018). This is particularly important given the evolving landscape of sustainable concrete technologies.

Computational Considerations

Deploying deep learning models in practical materials science settings, including on-site quality control or mobile laboratory environments, necessitates consideration of computational efficiency and resource constraints. Studies of deep learning on smartphones reveal that lightweight models, with optimized memory and computation footprints, can achieve real-time inference with minimal energy consumption (Xu et al., 2021). Model compression techniques, such as quantization and pruning, can be applied to tailor the model for deployment on edge devices or within embedded systems. Protection of intellectual property and prevention of unauthorized model extraction are also crucial considerations (Xu et al., 2021).

Interpretability and Conceptual Understanding

A persistent challenge in deep learning is the so-called "black box" problem the difficulty of interpreting the internal mechanisms and decision-making processes of complex neural networks (Lei et al., 2018). In materials science, where model predictions can influence high-stakes engineering decisions, interpretability is not merely desirable but essential.
Physics-inspired analyses propose that neural networks can be understood through the lens of quantum mechanics and statistical physics, with neurons acting as scattering sources and the network as a system evolving toward physically meaningful configurations (Lei et al., 2018). This analogy provides a promising avenue for demystifying the behavior of deep learning models in material applications.

Concept-Oriented Deep Learning for Materials

Concept-Oriented Deep Learning (CODL) offers a structured approach to embedding conceptual understanding within deep learning models (Chang, 2018). By associating learned feature representations with explicit material concepts such as "glass aggregate dispersion," "fiber bridging," or "ITZ porosity" the model's predictions can be rendered more transparent and actionable.
Concept graphs, constructed from domain knowledge and empirical data, serve as scaffolds for organizing feature representations and enabling incremental learning. Concept exemplars, drawn from typical instances of microstructural features, facilitate both supervised and unsupervised learning, supporting transferability and contextual adaptation.
Integrating CODL into the deep learning framework for microstructural prediction thus addresses critical limitations of standard models, including interpretability, transferability, and adaptability to new material scenarios.

Incremental and Continual Learning

In real-world materials research, data are often collected incrementally, and new material systems or processing techniques emerge over time. Incremental and continual learning methods, such as those implemented in iCaRL, enable deep learning models to adapt to new concepts without catastrophic forgetting (Chang, 2018). This ensures that knowledge gained from previous material systems is retained and leveraged when learning about new composites or process variations.
For example, as new types of glass or fiber aggregates are introduced, the model can incorporate their microstructural signatures into its concept graph,

updating its predictions and maintaining continuity with prior knowledge. This capability is vital for supporting innovation and rapid iteration in sustainable concrete technology development.

Predicting Mechanical Properties from Microstructure

A primary application of the proposed deep learning approach is the prediction of macroscopic mechanical properties such as compressive strength, modulus of rupture, and fracture toughness from microstructural data. By learning the complex, nonlinear relationships between aggregate distribution, fiber orientation, ITZ characteristics, and mechanical performance, the model can guide the design and optimization of concrete mixes. For instance, given a set of microstructural images and compositional data for a new concrete brick incorporating recycled glass and polypropylene fibers, the model can predict the expected strength and durability, accounting for the synergistic effects of aggregate shape, size, and dispersion.

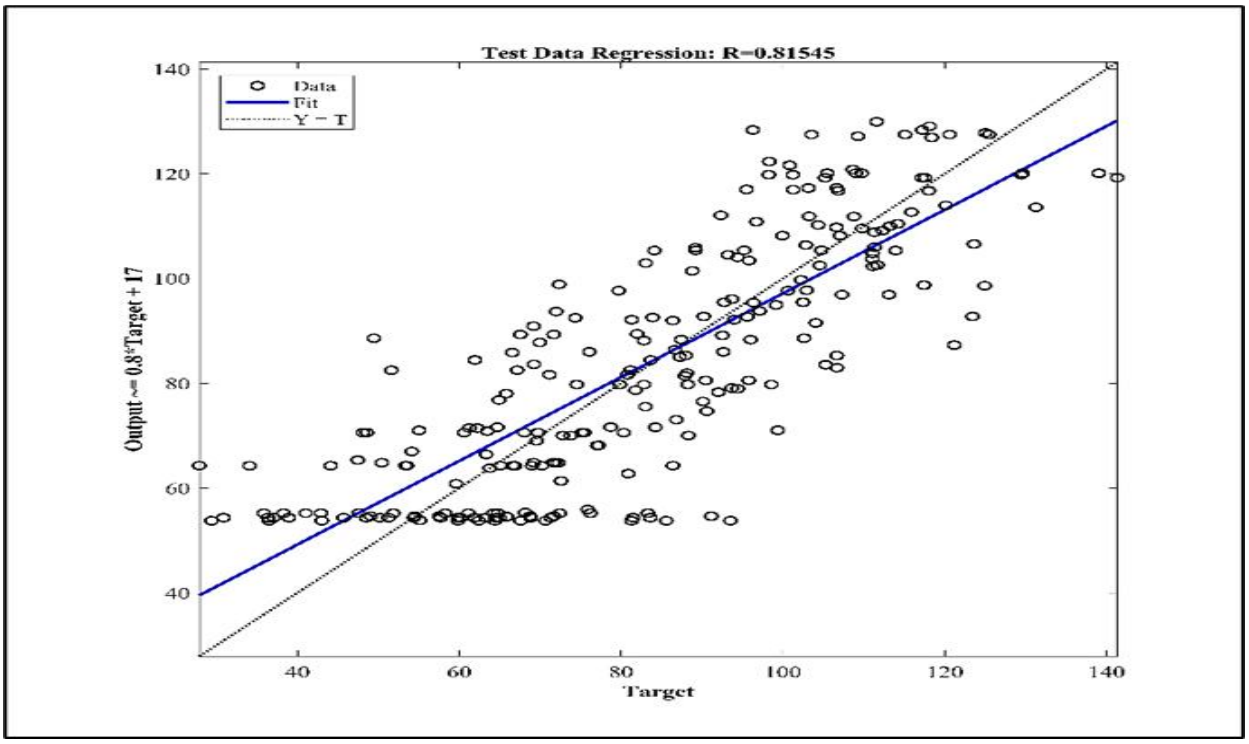

Figure: 1 Correlation between observed and predicted value of Compressive strength

Figure 1 illustrates the correlation between the observed and predicted values of compressive strength, highlighting the accuracy of the developed model in capturing the experimental results. The data points are closely distributed around the regression line, indicating a strong agreement between the actual and estimated values. The coefficient of determination (R^2) further confirms the reliability of the model, demonstrating its effectiveness in predicting compressive strength with minimal deviation from the measured values. This correlation plot provides clear evidence of the model's robustness and suitability for practical applications in concrete strength prediction.

IV. QUALITY CONTROL AND DEFECT DETECTION

Automated analysis of microstructural images using deep learning can significantly enhance quality control processes in concrete manufacturing. The model can be trained to detect defects such as voids, cracks, or agglomerations of glass particles, enabling real-time feedback and process adjustments.

Mobile deployment of lightweight models, as demonstrated in the context of smartphone applications, allows for on-site inspection and rapid decision-making (Xu et al., 2021). This democratizes

access to advanced analytical capabilities and supports the broader adoption of sustainable materials.

Design of Novel Composite Materials

The integration of concept-oriented deep learning with cross-attention-based multimodal fusion opens new avenues for the design of novel concrete composites. By simulating the effects of varying aggregate types, proportions, and processing parameters, the model can identify optimal configurations for targeted performance criteria.

Furthermore, the model's interpretability allows materials scientists to extract insights into the underlying mechanisms driving observed behaviors, fostering a cycle of hypothesis generation, experimentation, and refinement.

Advantages of the Deep Learning Approach

The deep learning framework outlined in this paper offers several advantages over traditional modeling approaches: Capacity for Nonlinear, Multiscale Modeling: Deep neural networks can capture complex, hierarchical relationships among microstructural features and macroscopic properties, surpassing the limitations of linear or simplified models. Automatic Feature Extraction: The model autonomously discovers salient features from raw data, reducing the reliance on handcrafted descriptors and domain-specific preprocessing. Multimodal Data Integration: Cross-attention mechanisms enable the fusion of diverse data types, supporting comprehensive and context-aware predictions. Interpretability and Knowledge Transfer: Concept-oriented modules facilitate mapping between learned representations and material concepts, enhancing interpretability and enabling knowledge transfer to new systems. Incremental and Continual Learning: The framework supports adaptation to evolving material landscapes, ensuring relevance as new technologies and materials emerge.

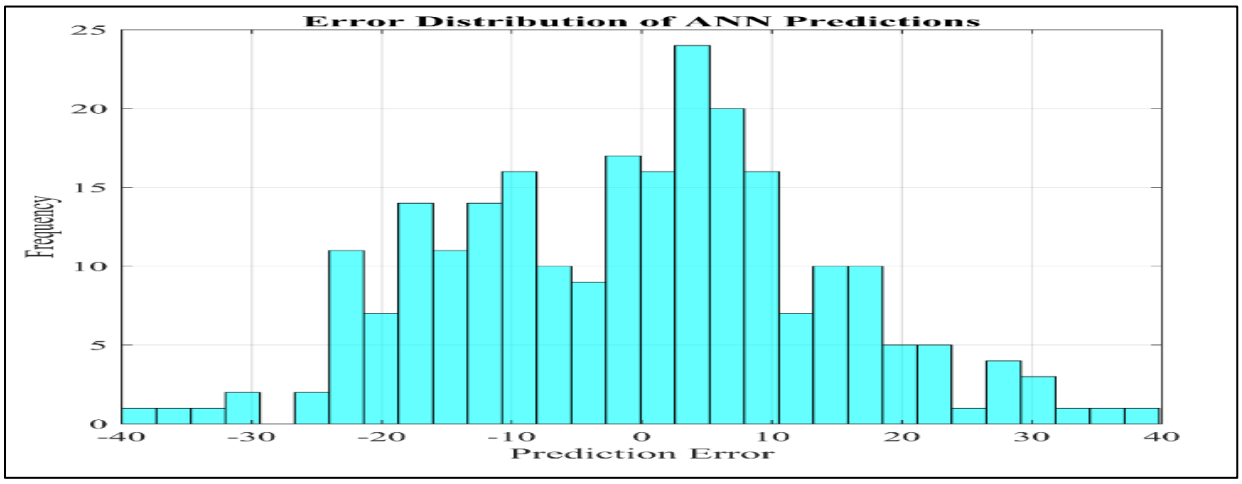

Figure:2 Predicted error vs frequency

Figure 2 presents the distribution of prediction errors plotted against their frequency, providing insights into the accuracy and consistency of the developed model. The majority of the errors are concentrated near zero, indicating that most of the predicted compressive strength values are in close agreement with the observed results. The symmetric and narrow spread of the error distribution reflects minimal bias and highlights the stability of the model. This error–frequency analysis further validates the model's robustness, as large deviations are rare and the overall prediction performance remains reliable.

Despite its promise, the deep learning approach also faces significant challenges:

Data Availability and Quality: Deep learning models require substantial, high-quality datasets for effective training. In materials science, such datasets can be difficult to acquire, particularly for novel or proprietary materials. Model Interpretability: While concept-oriented extensions improve interpretability, there remains a risk of overfitting or spurious correlations, especially when domain knowledge is insufficiently integrated. Computational Resources: Training and deploying deep learning models can be

resource-intensive, necessitating careful optimization for practical applications. Generalization and Robustness: Ensuring that models generalize beyond the training data to new material systems or environmental conditions is an ongoing challenge. Addressing these limitations will require continued collaboration between materials scientists, data scientists, and domain experts, as well as ongoing methodological innovation.

V. RESULT AND DISCUSSION

Physics-Informed Neural Networks (PINNs): Integrating explicit physical laws into deep learning architectures can enhance model generalization and interpretability (Lei et al., 2018). Self-Supervised and Unsupervised Learning: Techniques such as masked autoencoding and contrastive learning reduce reliance on labelled data and support broader applicability.

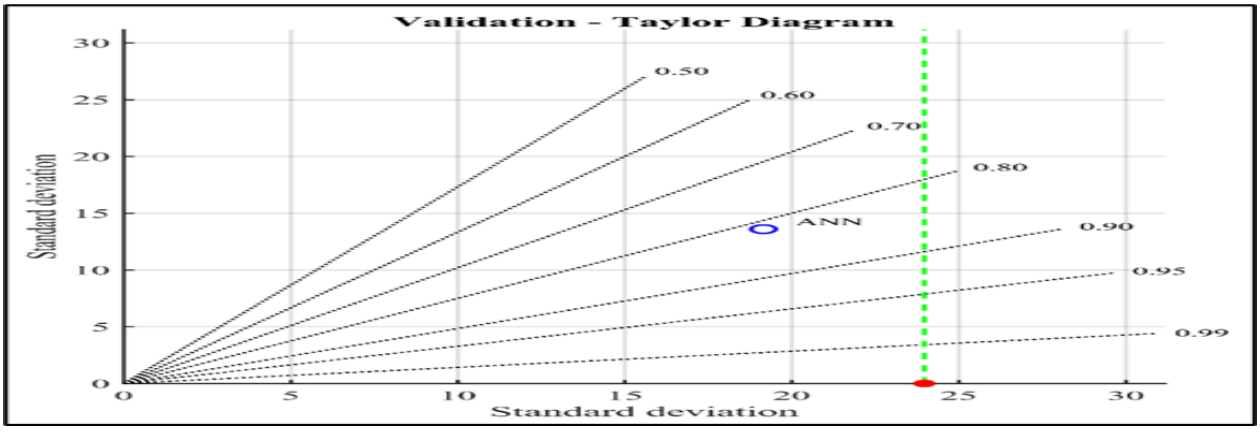

Figure:3 Taylor diagram for comparison of Strength prediction models

Figure 3 shows the Taylor diagram used to compare the performance of different strength prediction models in terms of their statistical accuracy. The diagram simultaneously presents the correlation coefficient, standard deviation, and root mean square error (RMSE) of each model, enabling a comprehensive evaluation of their predictive capabilities. Models that appear closer to the observed reference point demonstrate higher accuracy and stronger correlation with experimental data. This comparison highlights the relative efficiency of the models, helping to identify the most reliable approach for predicting compressive strength with minimal error.

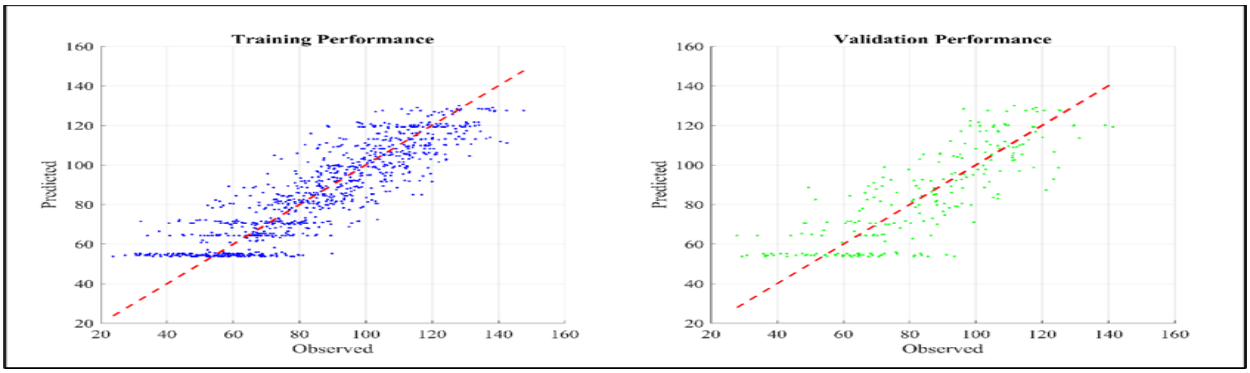

Figure: 4 Relation between predicted and calculated strength using

Figure 4 illustrates the relationship between the predicted and calculated compressive strength values obtained using the developed model. The data points are closely aligned along the line of equality,

confirming a strong agreement between the predicted outcomes and the calculated reference values. This close alignment indicates that the model is capable of producing accurate estimations with minimal deviation. The consistency observed in this relation further validates the reliability of the model and its applicability for practical strength prediction in concrete studies. Edge and Mobile Deployment: Advances in model compression and hardware acceleration enable the deployment of deep learning models in resource-constrained environments (Xu et al., 2021). Human-in-the-Loop Systems: Incorporating expert feedback into model training and interpretation can further improve reliability and trustworthiness. Continued research at the intersection of deep learning, materials science, and sustainability holds the potential to revolutionize the design and deployment of next-generation construction materials.

VI. CONCLUSION

The prediction of microstructural behavior in concrete bricks with glass and fiber aggregates is a complex, multifaceted problem at the nexus of materials science, engineering, and data analytics. Deep learning offers a transformative approach to this challenge, harnessing the power of hierarchical representation learning, multimodal data fusion, and conceptual understanding. By drawing on foundational theories of deep learning as physical systems (Lei et al., 2018), advances in cross-attention-based multimodal fusion (Seneviratne et al., 2025), and the imperative for interpretability via concept-oriented frameworks (Chang, 2018), this paper has outlined a comprehensive strategy for leveraging artificial intelligence in the advancement of sustainable, high-performance concrete composites. The integration of these methodologies enables the automatic extraction of salient features from diverse datasets, the fusion of complementary information streams, and the mapping of learned representations to meaningful material concepts. The resulting models not only achieve high predictive accuracy but also support knowledge transfer, contextual adaptation, and incremental learning qualities essential for driving innovation in sustainable construction. As deep learning continues to evolve, its application to materials science will be shaped by ongoing efforts to enhance interpretability, efficiency, and generalization. By embedding physical principles, conceptual understanding, and domain expertise within deep learning frameworks, researchers can unlock new possibilities for the design, characterization, and deployment of next-generation concrete materials, advancing both scientific understanding and practical sustainability.

REFERENCES

[1] Chang, D. T. (2018). Concept-Oriented Deep Learning. arXiv preprint arXiv:1806.01756v1. http://arxiv.org/pdf/1806.01756v1

[2] Lei, D., Chen, X., & Zhao, J. (2018). Opening the black box of deep learning. arXiv preprint arXiv:1805.08355v1. http://arxiv.org/pdf/1805.08355v1

[3] Seneviratne, G., Weerakoon, K., Elnoor, M., Rajgopal, V., Varatharajan, H., Jaffar, M. K. M., Pusey, J., & Manocha, D. (2025). CROSS-GAiT: Cross-Attention-Based Multimodal Representation Fusion for Parametric Gait Adaptation in Complex Terrains. arXiv preprint arXiv:2409.17262v3. http://arxiv.org/pdf/2409.17262v3

[4] Xu, M., Liu, J., Liu, Y., Lin, F. X., Liu, Y., & Liu, X. (2021). A First Look at Deep Learning Apps on Smartphones. arXiv preprint arXiv:1812.05448v4. http://arxiv.org/pdf/1812.05448v4

[5] Ervin, L., Bezawada, H., & Vikas, V. (2025). Improving Grip Stability Using Passive Compliant Microspine Arrays for Soft Robots in Unstructured Terrain. arXiv preprint arXiv:2502.12347v2. http://arxiv.org/pdf/2502.12347v/2

[6] A.E. Oke, et al., A capability assessment model for implementing digital technologies in Nigerian heavy construction firms, Smart Sustain. Built Environ. (2024). Kumar, P. and Singh, A., 2019. Groundwater contaminant transport modelling for unsaturated media using numerical methods (FEM, FDM). Int. J. Recent Technol. Eng. (IJRTE), 8(7), pp.2277-3878.

[7] Kumar, P., 2023. Detection of air pollution, air quality monitoring, and control using a wireless sensor network. In Recent Advancement of IoT Devices in Pollution Control and Health Applications (pp. 23-28). Woodhead Publishing.

[8] Kumar, P., 2023. IoT-based solid waste management and collection system using infrared sensors. In Recent Advancement of IoT Devices in Pollution Control and Health Applications (pp. 29-36). Woodhead Publishing.
[9] Kumar, S., Parhi, P.K., Kumar, P. et al. Zone-Wise Optimal Operation Policy and Evaluation of System Performance Measures. J. Inst. Eng. India Ser. A 102, 1129–1138 (2021). https://doi.org/10.1007/s40030-021-00553-w
[10] Roy, S. and Kumar, P., 2021. Comparative Review of Defluoridation Efficiency in Wastewater. International Journal of Prevention and Control of Industrial Pollution, 7(1), pp.15-21.
[11] J. Wang, et al., Synergistic utilization, critical mechanisms, and environmental suitability of bauxite residue (red mud) based multi-solid wastes cementitious
[12] materials and special concrete, J. Environ. Manag. 361 (2024) 121255.
[13] X. Liu, et al., Effect of carbonation curing on the characterization and properties of steel slag-based cementitious materials, Cem. Concr. Compos. 154 (2024)
[14] 105769.
[15] L. Su, et al., Creep characterisation and microstructural analysis of municipal solid waste incineration fly ash geopolymer backfill, Sci. Rep. 14 (1) (2024) 29828.
[16] L. He, et al., Development of novel concave and convex trowels for higher interlayer strength of 3D printed cement paste, Case Stud. Constr. Mater. 21 (2024)
[17] N. Farhan, et al., Effect of silica fume on the microstructural and mechanical properties of concrete made with 100% recycled aggregates, Rev. De. la
[18] ConstruccioN. ´ 23 (2) (2024) 413–435.
[19] M. Khan, M. Ali, Effect of super plasticizer on the properties of medium strength concrete prepared with coconut fiber, Constr. Build. Mater. 182 (2018) 703–715.
[20] M. Khan, A. Rehman, M. Ali, Efficiency of silica-fume content in plain and natural fiber reinforced concrete for concrete road, Constr. Build. Mater. 244 (2020)
[21] M.H.R. Sobuz, et al., Assessing the influence of sugarcane bagasse ash for the production of eco-friendly concrete: experimental and machine learning approaches, Case Stud. Constr. Mater. 20 (2024).
[22] Y. Jiang, et al., A critical review of waste glass powder–multiple roles of utilization in cement-based materials and construction products, J. Environ. Manag. 242 (2019) 440–449.
[23] D. Qin, Y. Hu, X. Li, Waste glass utilization in cement-based materials for sustainable construction: a review, Crystals 11 (6) (2021).
[24] T. Dai, et al., Waste glass powder as a high temperature stabilizer in blended oil well cement pastes: hydration, microstructure and mechanical properties, Constr. Build. Mater. 439 (2024).
[25] F.S. Aditto, et al., Fresh, mechanical and microstructural behaviour of high-strength self-compacting concrete using supplementary cementitious materials, Case Stud. Constr. Mater. 19 (2023) e02395.
[26] A.A. Aliabdo, M. Abd Elmoaty, A.Y. Aboshama, Utilization of waste glass powder in the production of cement and concrete, Constr. Build. Mater. 124 (2016)
[27] Y. Liu, et al., State-of-the art on preparation, performance, and ecological applications of planting concrete, Case Stud. Constr. Mater. 20 (2024).
[28] L. Yang, et al., Three-dimensional concrete printing technology from a rheology perspective: a review, Adv. Cem. Res. 36 (12) (2024) 567–586.
[29] M. Habibur Rahman Sobuz, et al., Performance of self-compacting concrete incorporating waste glass as coarse aggregate, J. Sustain. Cem. Based Mater. 12 (5)
[30] N.M.S. Hasan, et al., Utilization of waste glass cullet as partial substitutions of coarse aggregate to produce eco-friendly concrete: role of metakaolin as cement
[31] replacement, Sustainability 15 (14) (2023).
[32] C. Chen, et al., Waste E-glass particles used in cementitious mixtures, Cem. Concr. Res. 36 (3) (2006) 449–456.