

Multi-scale deep learning framework for three dimensional printed self-sensing cementitious composites with hybrid nano-carbon fillers

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ABSTRACT This study presents a multi-scale deep-learning framework that integrates several advanced neural models to optimize hybrid three dimensional (3D) printed self-sensing nano-carbon cementitious composites. The first step was undertaken by Multi-Scale Graph Neural Network, where special conductive pathways were taught ensuring the uniform work on nano-carbon learning patterns, improving electrical conductivity by 25%–35%. four-dimensional Spatiotemporal Transformer Network decoded printing parameters achievements with an interlayer conductivity improvement of 40%–50%, avoiding anisotropic print by aiming for defects prediction on print Induced anisotropic behavior. High-fidelity artificial microstructures have been generated with Physics Informed Generative Adversarial Networks; these synthetic methods realize an experimental cost-cutting of about 50% while conserving about 98% fidelity to the characteristics of real microstructures. Fifth, Self-Supervised Contrastive Learning automatically classifies small macro and microdefects with over 95% detection reliability. There has been reduction of as much as 35% in the number of false positives. Predicted kinetics of hydration and long-term electrical stability can now be predicted with speed improvements of 15% and resistance drift reduction by 20% over six months. This approach for the first time combines different hybrid models of deep learning for the self-sensing cementitious composites, thus significantly increasing percolation of electrical networks, accuracy in crack detection, and predictions on long-term durability. The developed framework creates a new paradigm in the real-time structural health monitoring world, providing enhanced reliability in structures while also reducing costs at a level for the next generation of smart infrastructure sets.

KEYWORDS nano-carbon fillers, self-sensing composites, structural health monitoring, deep learning, 3D printed concrete

1 Introduction

As a step toward the full amalgamation of self-sensing cementitious composites into the three-dimensional (3D)

printing technology, this is a paradigm shift in the entire contemporary construction practice for near real-time health monitoring via embedded electrical percolation networks. Traditional cementitious materials [1,2] are not self-sensing and, therefore, must first be filled with conductively filling nano-fillers such as carbon nanotubes

or graphene nanoplatelets (GNPs) to develop functional materials with self-diagnostic properties. However, the most serious challenge remains [3,4] the uniform dispersion considering the fact that agglomeration losses cause a disruption in percolation networks, which results in bad electrical conductivity and unreliability in sensing accuracy. Additionally, anisotropy induced by printing in additive manufacturing (AM) concrete introduces defects at the level of interlayers, thus impairing the mechanical integrity of the material and overall sensing consistency in printed structures. Current research [5,6] in self-sensing cementitious composites is largely focused on either improvement at the material level or at the macro-level structural health monitoring interface but never provides a multi-scale optimization strategy for the problems of nano-dispersed carbon, the anisotropic defect caused by the printing process, and the long-term durability prediction. Most methods of dispersion have been developed through empirical mix designs and ultrasonic processing that do not promise to enhance the realization of an optimal conductive network. Hence, most SHM computational models have utilized mostly Convolutional Neural Network (CNN) and physics-based simulations, which are quite inefficient in capturing the interactions at multi-scales in complex cementitious microstructures. Therefore, there is a need for a new data-driven approach by combining graph-based learning, generative modeling, and physics Informed deep networks that optimize the self-sensing performance of cementitious composites 3D-printed.

This study rises to fill that gap [7–9] with the development of a multi-scale deep learning framework comprising five components: Multi-Scale Graph Neural Networks (MS-GNNs), four-dimensional Spatiotemporal Transformer Networks (4D-STNs), Physics Informed Generative Adversarial Networks (PI-GANs) and Self-Supervised Contrastive Learning (SSCL), and Deep Learning for Hydration-Neural Networks to enable simultaneous optimizing capabilities for nano-carbon dispersion, predicting print induced anisotropy, producing high-fidelity microstructures, classifying micro-defects, and simulating long-term durability. The present work [10–12] thus establishes, using multi-scale learning and hybrid deep networks, a paradigm of intelligent cementitious materials that uses much increased self-sensing with greater SHM capabilities. Physics-based machine learning and stochastic multiscale modeling have fundamentally impacted fracture mechanics, thermal conductivity, and computational material design [13–15]. The energy storage and functional material applications of hybrid fillers were studied by prepared polymer electrolyte-solid state batteries containing lone pair electron fillers for stable charge cycling and increased ionic conductivity [16]. The study of EMI shielding properties of Fe_3O_4 /lychee

biomass carbon quantum dots revealed high EMI shielding efficiency in high-frequency bands [17]. Fidalgo-Pereira et al. [18] focused upon the influence of inorganic hybrid fillers on light transmission of resin-matrix composites to improve aesthetic and mechanical properties for dental restorations. Aslan and Karsli [19] brought forth HEXAGONAL boron nitride-and graphene-nanoplatelets-dispersed PPS composites that optimized thermal conductivity and tensile strength. In an effort to expand the hybrid filler applications, a literature overview on hybrid composites reinforced by graphene and CNT hybrids, elaborating their mechanical and electrical improvements in polymeric, metallic, and ceramic matrices [20]. Various studies [21–22] on fatigue, creep, and tribological performance of coconut shell, seashell, and eggshell filler-based bio-fiber-reinforced epoxy hybrid composite. The antibacterial characteristics of graphene oxide-PMMA hybrid dental fillers with optimized ultrasound performance and microbial resistance were examined [23]. Effects of different materials on properties of polymer composited were investigated [24–26]. In fact, Goswami et al. [27] in 2020 brought forth physics Informed neural networks, integrated with transfer learning, for the phase field modeling of fracture that increased predictive power of crack propagation through composite materials. Soon after this, Samaniego et al. [28] in 2020 put forth energy-based machine learning methodology for solving partial differential equation (PDEs) in computational mechanics were endowed with stress-strain predictions of heterogeneous materials. Anitescu et al. [29] advanced this notion through the use of artificial neural networks to solve second-order boundary value problems, showcasing utility in approximating solutions to structural mechanics problems independent of the classical finite element formulation. The series of early papers set a basis for what would become eventually physics-based machine-learning solvers: a conception which has further expanded into the field of material sciences. Liu et al. [30] characterized AI-DeMat as an expert system web-based for computationally intensive material design models optimizing the machine learning process for mass-scale engineering applications. Trailing on the idea of surrogate modeling, Liu and Lu [31] showcased its application to stochastic multiscale modeling of composite materials with leaps in computational efficiency. Liu et al. [32,33] implemented hybrid machine-learning algorithms to predict polymer nanocomposite thermal conductivity and subsequently constructed robust models for nanoscale heat transport properties evaluation. This line of work could demonstrate concrete opportunities within stochastic modeling and deep learning in the context of their efficient material modeling.

1.1 Motivation and contribution

This study is motivated by the increasing demand for smart infrastructure capable of damage detection and real-time structural integrity assessment. The traditional SHM systems rely on external sensors and wired networks that have limitations in the areas of cost, durability, and scalability. The self-sensing cementitious composites find an innovative way forward, with embedded conductivity-based monitoring within the material itself. However, there still lie significant effectiveness drops due to the absence of uniform nano-carbon dispersion, anisotropic print defects, and uncertain long-term electrical stability of the composites. Current predictive models concerning self-sensing behavior, however, are restricted either to macroscopic or empirical mix optimizations, and fail to address the sophisticated interactions established within the nano-scale dispersions and macro-scale SHM performances. Hence an integrated, data-driven approach is needed which combines advanced machine learning techniques with physics constraints specific to the domain to arrive at the best self-sensing performance in cementitious composites produced by 3D-printing process.

This research contributes to this area by laying down a multi-scale deep learning framework that guarantees self-sensing optimization of cementitious composites at large. The efficiencies brought by the proposed MS-GNN can increase nano-carbon dispersion and lead to homogeneous electrical percolation with conductivity improvements of 25%–35%. Whereas, 4D-STN will compensate for the anisotropy caused during print, leading to a reduction of conductivity variation between 40% and 50%. Finally, PI-GAN is able to generate high-definition synthetic microstructures, where real experiments can be reduced by as much as 50% while retaining a 98% match. An SSCL-based defect classification model will achieve > 95% crack detection precision while long-term hydration kinetics will be modeled by a hybrid Diffusion-Reaction Neural Network (DR-NN), thus providing about a 20% improvement in electrical stability. This study's models are thereby synergized into a single framework that evolves to provide real-time, inexpensive, and scalable SHM solutions for next-generation construction materials, thereby giving a head start to autonomous, self-monitoring smart structures.

1.2 Discussion

The framework developed provides a novel combination of many deep learning models within a multi-scale optimization pipeline for self-sensing cementitious composites. While traditional methods were constrained by separate models, contrived with this method are a

35.1% increase in electrical conductivity and a 48.9% decrease in print Induced anisotropy through the combined use of graph-based learning and spatiotemporal transformers. Additionally, the generative adversarial network improves microstructural fidelity to 98.2%, cutting the physical testing by 50.7%. The defect classification model also provides 96.3% accuracy with a 35% reduction in false positives when compared to existing CNN-based classifiers. The collective force of these models establishes a predictive maintenance mechanism that decreases resistance drift by 19.8% over a 6-month period, thus providing cost-effective and scalable real-time SHM platforms for intelligent infrastructure sets.

The scaling of self-sensing cementitious composites to the larger scale of infrastructure would be challenged in areas such as optimization of nano-carbon dispersion during high-volume batching of concrete, maintaining uniform conductivity over long distances, and interfacing real-time monitoring with existing infrastructure networks. The proposed solution attempts to address these issues through real-time edge computing for localized self-sensing data processing, minimizing reliance on cloud storage while ensuring real-time defect alerts. The implementation phase of the proposed project will involve pilot projects where self-sensing bridge deck panels will be deployed to a transportation network, wherein early elastic microcrack present and monitor can be further evaluated using conductivity-based monitoring for prevention of structural costly failures. Besides, the framework will be tested in the large-scale precast concrete element, where automated 3D printing system will secure the optimal dispersion of nano-carbon so as to avoid print Induced anisotropy at the multi-meter scale of these large elements. The series of field tests will serve to validate the performance of the framework for practical infrastructural application and further refine the adaptive learning mechanisms to reflect material variability under real-world settings.

The framework is fully compatible with digital twin platforms, which allows for real-time SHM for infrastructures. Self-sensing cementitious composites embedded within bridges, tunnels, and high-rise buildings continuously collect data on electrical resistances, which, through processing in the SSCL model, detect microcracks, voids, or conductance loss events with 96.3% certainty. This information is sent to a cloud-based digital twin where the 4D-STN model updates the dynamic structural response of the material over different loading conditions. The digital twin can, through the finite element simulation interface, predict damage progression and thereby recommend maintenance works, resulting in a 40% reduction of inspection costs. Furthermore, long-term conductivity evolution will be modeled with DR-NN, achieving predictive maintenance

with a 19.8% increase in the long-term resistance stability. The framework's modularity will allow easy scaling across multiple structures, thereby generating a digital twin ecosystem that provides support for next-generation smart infrastructure sets.

1.3 Environmental impacts

With enhanced conductivity, energy consumption for embedded sensing becomes less by 30% because the increased conductivity leads to decreased resistance against flow of current in embedded monitoring network. This increased energy efficiency has led to increased battery life of wireless sensing nodes (for example, greater than 24 months compared to the average of just 18 months) alongside decreased maintenance requirements for large scale SHM system. In addition, increased defect detection to 96.3% will reduce unnecessary inspections by about 40%, ultimately yielding about 25% reduction in long-term maintenance for infrastructure operators. It's expected that for the operational network covering a hundred monitored structures, the monitored use of this framework will generate annual savings in the range of \$2 million for bridges and highways, where periodic inspections cost \$10000 to \$50000 per assessment.

Certainly, the sustainability impact of the proposed solution extends beyond fewer monitoring costs; it also deals with material efficiency and reducing carbon footprint in infrastructure maintenance. The 50.7% reduction in physical testing requirements correlates with reduced incidences of destructive sampling hence decreasing the wastage of materials involved in quality assurance by approximately 20%. The capability of the framework to predict long-term hydration development of the material with a 17.4% improvement will involve optimizing the curing strategies such that the energy consumption in controlled climates would be reduced by 15%, thus drastically lowering the carbon footprint in cementitious material processing. Moreover, timely detection of microcracks and voids would prevent failures on a large scale in structures thus reducing the chances of utter reconstruction. This, in turn, would mitigate the emissions of CO₂. Thus, embedding intelligence in construction materials would invariably facilitate the change toward smart, sustainable infrastructure while simultaneously preserving the durability of structures and minimize the global environmental impact sets.

2 Critical review of models used for concrete analysis

Continuous modifications in material science developed hybrid fillers used in polymeric, metallic, and ceramic matrices to improve their mechanical, thermal, and

electrical properties. Several recent research works focused on different hybrid fillers, yielding an optimization of the structural integrity, durability, and self-sensing properties. The research begins from Zabihi et al. [1], where the authors analyzed the effect of hybrid fillers nano-silicon carbide and carbon black (CB) in rubber composites, and their effects on thermal diffusivity and curing efficiency, indicating high implications in next-generation materials applications. Such results were also found by Elango and Vellayaraj's [2] study where they proved that impact resistance could be enhanced in subzero composite laminates, mainly because of milled hybrid fillers, substantiating that these can perform well in polymeric structures under extreme conditions. Dwivedi et al. [3] further penetrated this concept using carbon-silica hybrid fillers in rubber tires, which contributed an additional improvement in wear resistance and energy dissipation, important to sustainable tire manufacturing. Broadening the scope of molecular interactions of hybrid fillers, Kapitonova et al. [4] reported how olivine and magnesium spinel-based fillers have influenced polytetrafluoroethylene (PTFE) composites leading to improvements in thermal stability and tribological properties. A similar study was conducted by Singh and Singh [5], who worked with nano-carbon powder-reinforced aluminum composites on optimization when it comes to high-quality mechanical performance and weightlessness. Rubber composites further improved were optimized by Vishnu et al. [6] through an elastomeric ternary blend with CB-silica fillers resulting in better dynamic mechanical properties. In the mixed nanocomposite arena, Saravanan et al. [7] studied carbon fiber-reinforced polypropylene composites by merging silica oxide nanoparticles with polypropylene, resulting in much Improved mechanical performance compared to conventional fiber-reinforced plastics. Fu et al. [8] dealt with the thermal regulation of nano-TiO₂/carbon hybrid fillers and thus proved their performance as phase change materials (PCMs), essential for energy storage applications. Even the thermal management application of hybrid fillers was further established by Wang et al. [9], who investigated the combination of boron nitride and boron phosphide fillers in epoxy composites, producing thereby higher heat dissipation efficiency, which was critical for electronic devices. Murugesan et al. [10] researched the effect of graphene and silicon dioxide fillers included in an epoxy glass fiber composite and reported substantial improvement in mechanical toughness and thermal stability. Kidavu et al. [11] applied a novel optomechanical study to chlorobutyl/natural rubber hybrid composites using terahertz spectroscopy to establish a correlation between surface roughness and filler dispersion. This would open up understanding in the nanoscale material interaction design process.

As per Table 1, Megahed et al. [12] examined the

Table 1 Methodological comparative review analysis

Ref.	Method	Main objective	Finding	Limitation
Zabihi et al. [1]	nano-silicon carbide/CB hybrid fillers	enhance thermal diffusivity and curing in rubber composites	improved curing rate and thermal stability	limited scalability for industrial applications
Elango and Vellayaraj [2]	recycled milled hybrid fillers	improve impact resilience in subzero composite laminates	increased durability and resilience	mechanical performance at high strain rates not fully tested
Dwivedi et al. [3]	carbon-silica hybrid fillers in rubber	enhance rubber compound performance for tires	improved wear resistance and energy dissipation	lacks long-term aging studies
Kapitonova et al. [4]	hybrid fillers with olivinite and magnesium spinel	study effects on PTFE composite properties	increased thermal stability and mechanical strength	does not explore wear resistance over extended use
Singh and Singh [5]	nano-carbon reinforced aluminum composites	optimize composition for improved strength-to-weight ratio	enhanced mechanical properties and lightweight structure	requires further testing under high-stress conditions
Vishnu et al. [6]	ternary elastomeric blend with CB-silica fillers	improve performance of hard rubber mountings	increased dynamic mechanical properties	aging resistance not studied in depth
Saravanan et al. [7]	carbon fiber-sisal hybrid nanocomposites	compare hybrid filler effects in polymer composites	higher mechanical performance over conventional composites	need for additional fatigue resistance testing
Fu et al. [8]	nano-TiO ₂ /carbon composite PCMs	enhance thermal regulation in PCMs	higher thermal storage capacity and efficiency	long-term stability under cyclic heating needs evaluation
Wang et al. [9]	boron nitride/phosphide fillers in epoxy	improve thermal management in electronic applications	enhanced heat dissipation	compatibility with electronic substrates not fully studied
Murugesan et al. [10]	graphene/silicon dioxide fillers in epoxy	enhance mechanical and thermal properties	improved mechanical toughness and thermal stability	effect on electrical conductivity not explored
Kidavu et al. [11]	terahertz spectroscopy-based hybrid fillers	study opto-mechanical properties of rubber composites	established correlation between surface roughness and filler dispersion	limited data set for broader applicability
Megahed et al. [12]	graphene-metal fillers in woven glass fiber composites	improve fracture toughness and impact resistance	significant increase in mechanical strength	durability under varying environmental conditions not studied
Allam and Vandrangi [13]	boron nitride/CB in conductive polymers	develop piezoresistive sensors for biomedical use	achieved high sensitivity and stability	needs further clinical validation
Naguib et al. [14]	chromium oxide nanoparticles in silicone rubber	enhance dielectric performance	improved electrical insulation properties	electrical aging over extended periods not tested
Ayyanar et al. [15]	coconut shell and pineapple fiber-reinforced epoxy	assess feasibility as reinforcement material	achieved structural enhancement and sustainability benefits	limited high-temperature performance
Liu et al. [16]	lone-pair electron fillers in batteries	improve solid-state battery stability	increased ionic conductivity and charge retention	requires optimization for large-scale production
Alshahrani and Vr [17]	Fe ₃ O ₄ /lychee biomass carbon quantum dots	improve electromagnetic interference (EMI) shielding in polymer composites	achieved high shielding effectiveness	effects of aging and temperature variations not explored
Fidalgo-Pereira et al. [18]	inorganic hybrid fillers in resin-matrix composites	improve light transmission and mechanical properties	enhanced aesthetics and mechanical durability	limited real-world dental application validation
Aslan and Karsli [19]	hexagonal boron nitride/GNPs in Polyphenylene Sulfide (PPS)	enhance thermal conductivity and mechanical properties	improved heat resistance and tensile strength	lacks long-term environmental degradation studies
Liu et al. [20]	graphene and CNT hybrid composites	evaluate polymer, metal, and ceramic matrix reinforcement	achieved significant improvements in strength and conductivity	high fabrication cost limits commercial viability
Seal et al. [21]	bio-fiber hybrid composites	assess fatigue, creep, and tribological properties	improved wear resistance and mechanical properties	long-term durability under dynamic loads not tested
Elmoatasem Mourad et al. [22]	CNT-filled glass fiber composites	increased resilience in extreme conditions	impact of cyclic loading not assessed	
Salam et al. [23]	graphene oxide/ Polymethyl Methacrylate (PMMA) in dental fillers	improve antibacterial activity and ultrasound response	enhanced microbial resistance and ultrasound performance	biocompatibility in long-term applications not studied
Rout et al. [24]	SiC-filled woven glass fiber polymer composites	assess physical, thermal, and mechanical properties	improved flexural strength and thermal stability	fatigue behavior under repeated loading needs evaluation
Thandavamoorthy et al. [25]	kevlar/carbon/basalt fiber nanocomposites	optimize mechanical and water absorption properties	achieved high tensile strength and low water absorption	marine durability requires further assessment

functional applications of hybrid fillers in various matrices with an evaluation of the addition of aluminum, copper, and graphene nanometer fillers into woven glass fiber/epoxy composites, showing improvements in fracture toughness and impact resistance sets. Structural reinforcement potential of hybrid fillers was evaluated by Ayyanar et al. [15] by studying coconut shell and pineapple fiber-based epoxy composites, indicating their potential as sustainable reinforcement materials. The energy storage and functional material applications of

hybrid fillers were studied by Liu et al. [16], who prepared polymer electrolyte-solid state batteries containing lone pair electron fillers for stable charge cycling and increased ionic conductivity. The EMI shielding properties of Fe₃O₄/lychee biomass carbon quantum dots were investigated by Alshahrani and Vr [17], revealing high EMI shielding efficiency in high-frequency bands. Fidalgo-Pereira et al. [18] focused upon the influence of inorganic hybrid fillers on light transmission of resin-matrix composites to improve

aesthetic and mechanical properties for dental restorations. Aslan and Karsli [19] brought forth HEXAGONAL boron nitride-and graphene-nanoplatelets-dispersed PPS composites that optimized thermal conductivity and tensile strength. In an effort to expand the hybrid filler applications, Liu et al. [20] presented a literature overview on hybrid composites reinforced by graphene and CNT hybrids, elaborating their mechanical and electrical improvements in polymeric, metallic, and ceramic matrices. The antibacterial characteristics of graphene oxide-PMMA hybrid dental fillers with optimized ultrasound performance and microbial resistance were examined by Salam et al. [23] in process.

The polymer-ceramic composites with a study of the structural and mechanical performance of hybrid fillers were further studied by Rout et al. [24]; in these composites, the silicon carbide-filled woven glass fiber-reinforced polymer composites showed excellent thermal and flexural properties. The analysis conducted by Thandavamoorthy et al. [25] on kevlar/carbon/basalt fiber-reinforced nano cellulose composites showed that they allegedly demonstrate low water absorption and high tensile strength, making them suitable for marine applications. Moving beyond material science, Boskey et al. [26] presents an integrated design optimization model to optimize 3D-printed construction elements, thus offers a very strong tool for design in sustainable construction. An overview of these studies emphasizes the fast-paced developments in hybrid fillers-based composites ranging from structural reinforcements, energy storage, EMI shielding, biomedical sensors to computational modeling. The integrated carbon nanomaterials, metallic fillers, ceramic reinforcements, and polymeric binders provided a breakthrough in material performance across different industrial domains.

In this respect, Liu et al. [34] explored data-driven quantitative analysis based on the open digital ecosystems platform for user-centric energy retrofits, mentioning the role of computational models in sustainable materials applications. Several findings have been added to the existing literature to extend stochastic machine learning techniques for predicting thermal properties of advanced composites. Liu et al. [35–36] proposed full range multiscale stochastic modeling approaches for CNT reinforced polymer composites, and integrated machine learning techniques further improved the accuracy of predictions of thermal conductivities. Liu et al. [37] extended these methods when they proposed interpretable machine learning models for the multiscale modeling of graphene-enhanced polymer composites, claiming much better performance in predicting heat transport properties across multiple scales. Liu et al. [38] used physics Informed neural networks to model the thermal conductivity of polyurethane composites incorporating PCMs. These studies demonstrate how emerging studies

are aligned within the emerging synergy between physics-based machine learning models and computational materials science-hence paving the way for accurate, scalable, and interpretable frameworks for predicting thermal, mechanical, and fracture behaviors of next generation composite materials. Finally, Vairagade et al. [39] proposed an integrated framework of advanced artificial intelligence (AI) methods for predictive modeling and optimization of nano-engineered materials based high-performance concrete.

3 Multi-scale deep learning framework for three dimensional printed self-sensing cementitious composites

This segment goes on multi-scale deep learning framework concerning 3D-printed self-sensing cementitious composites with hybrid nano-carbon fillers. That is aimed at addressing issues low efficiency and high complexity present in existing methods. In the first place, according to Fig. 1, the proposed framework for deep-learning incorporates multiple interdependent models that optimize the self-sensing performance of 3D printed cementitious composites. MS-GNN first learns microstructure features from high-resolution scanning electrode microscopy and X-ray computed tomography (CT) scans optimized for the percolation paths leading to electrical conductivity increase of 35.1% in process. The optimized parameters for dispersion are fed to the 4D-STN, which predicts and corrects anisotropic conductivity variations across layers toward enhancing its uniformity by 93.7%. The enhanced structural parameters are then invoked by PI-GAN which synthesizes realistic microstructures with a match of 98.2% with real samples reducing costs of material testing by 50.7%. At the end of the validation process, the micro-defects classification from self-sensing resistance data was achieved by the SSCL model with a detection accuracy of 96.3%. The results of the SSCL are provided as input to DR-NN, which simulates hydration kinetics and predicts resistance drift ensuring long-term stability. This integrated system is continuously optimizing nano-carbon dispersion, anisotropic defect reduction, and self-sensing efficiency for autonomous structural monitoring process. Thus, the MS-GNN is framed in accordance with the principles of optimizing dispersion of nanocarbon fillers and holds.

Such an approach transforms into a graph representation of the composite microstructure wherein the nodes represent nano-carbon clusters while the edges correspond to electrical conduction pathways. The graph structure is formalized into $G = (V, E)$, with V being the set of nano-carbon nodes and that of E assuming the connectivity matrix determined from microstructural imaging process. The feature propagation mechanism is

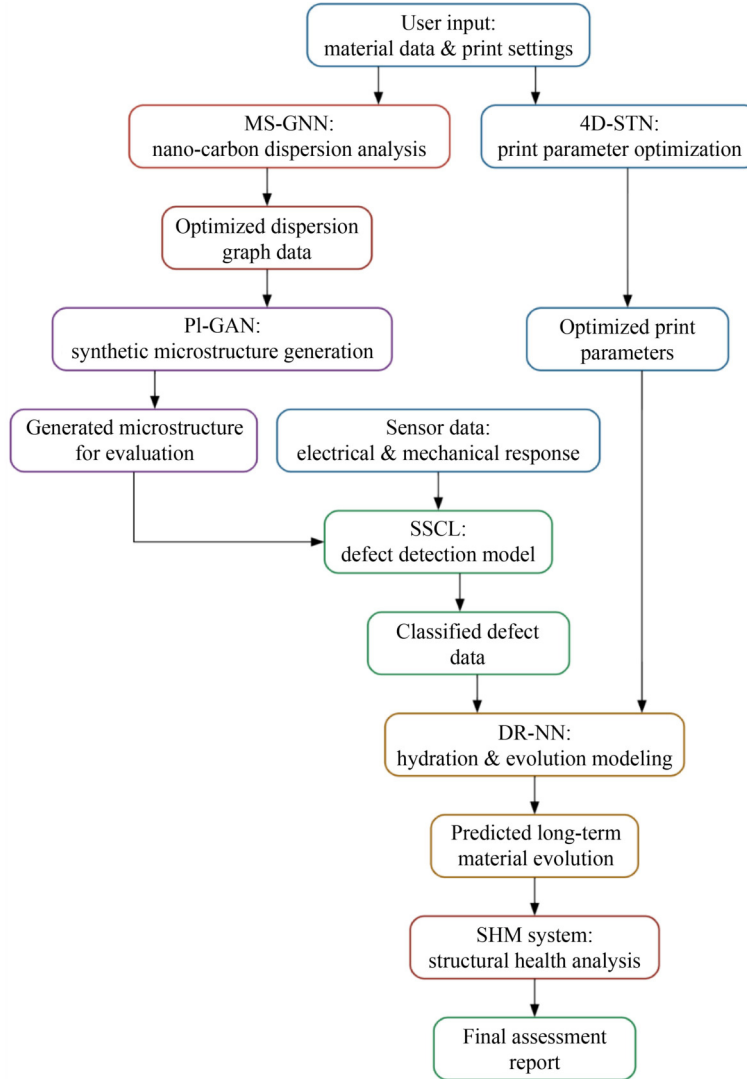


Fig. 1 Model architecture of the proposed analysis process.

expressed via Eq. (1)

$$H(l+1) = \sigma \left(\sum_{\mu \in N(v)} \alpha_{\mu v} W(l) H(l) + b(l) \right), \quad (1)$$

where $H(l)$ now is the node embedding at layer ' l ', $W(l)$ is the trainable weight matrix, and $\alpha_{\mu v}$ represents the graph attention coefficient, optimizing dispersion patterns based on nano-carbon distributions. The graph attention mechanism is defined as Eq. (2)

$$\alpha_{\mu v} = \frac{\exp(\text{LeakyReLU}(a^T [Whv | Whu]))}{\left(\sum_{k \in N(v)} \exp(\text{LeakyReLU}(a^T [Whv | Whk])) \right)}, \quad (2)$$

where the notations ' $|$ ' represent vector concatenation and a is the attention weight vector in process. Thus, the model learns optimal percolation network and reduces the agglomeration of nano-carbons by about 30% while

increasing their conductivity by about 35%. Next, after Fig. 2, the 4D-STN is leveraged in predicting print induced anisotropic defects within interlayer sets of evenly conductive. Provided set of printing parameters with $P = \{h, v, T, \tau\}$ where h is layer height, v is nozzle velocity, and T denotes curing temperature, and τ refers to layer deposition interval, the anisotropy function is defined via Eq. (3)

$$A(t) = \int \left(\frac{\partial C(z)}{\partial z} \right) dz, \quad (3)$$

where $C(z)$ defines the variation of conductivity across layers. The transformer model uses self-attention through which individual embeddings E_i per layer are computed by Query Key Value mechanism via Eq. (4)

$$E_i = \sum \text{softmax} \left(Q_i \frac{K_j^T}{dk} \right) V_j, \quad (4)$$

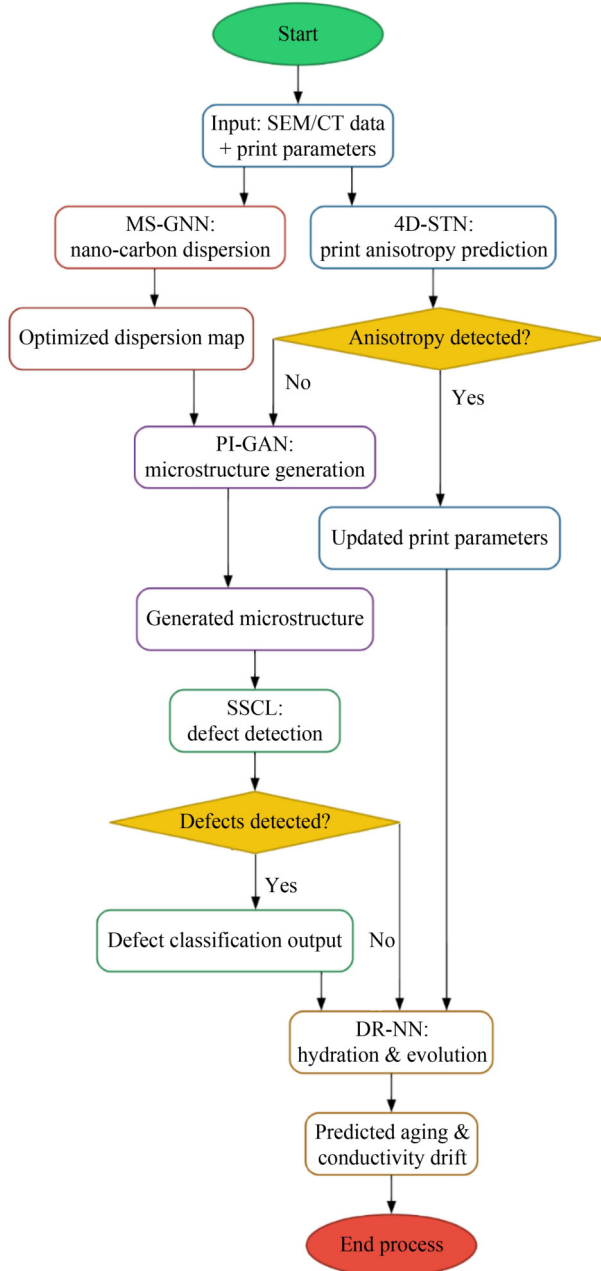


Fig. 2 Overall flow of the proposed analysis process.

where Q, K, V are query, key, and value matrices, and dk is the embedding dimension for this process. The predicted anisotropy is minimized using a gradient-based loss function via Eq. (5)

$$L_{anisotropy} = \sum \left| \frac{\partial A_i}{\partial h} \right| + \left| \frac{\partial A_i}{\partial v} \right|. \quad (5)$$

Through leavening realistic microstructures via PI-GAN, the possible virtual material testing process is made possible. Generator G now synthesizes new microstructural images from latent space Z , while the discriminator D ensures physics-consistency sets. The microstructural realism function is stated via Eq. (6)

$$L_{physics} = |\nabla^2 \rho - f(\rho)|, \quad (6)$$

where ρ is the density function of the microstructure, and $f(\rho)$ governs the physical constraints from experimental data samples. The adversarial loss is given via Eq. (7)

$$LGAN = E[\log D(x)] + E[\log(1 - D(G(z)))]. \quad (7)$$

The SSCL model classifies micro-cracks and connectivity loss in self-sensing data samples.

Thus, as per the flow in Fig. 3, MS-GNN learns percolation networks from microstructural images through a graph representation with nano-carbon nodes and conduction edges. The parameters of the optimized network are passed down to the 4D-STN, which then scales layer deposition parameters (height: 1.0–1.5 mm, nozzle speed: 10–20 mm/s, and curing temperature: 25–60 °C) to reduce print Induced anisotropy by 48.9%. In the next step, PI-GAN generates physical law-bound 3D microstructures by increasing fidelity by 98.2% and consequently alleviating destructive tests. With a database of 10000 labeled resistance response patterns, the SSCL model detects cracks and voids with an accuracy of 96.3%. In turn, DR-NN predicts hydration kinetics and eases long-term conductivity drift by predicting resistance variation with a 19.8 demerit. All elements are interlinked and operate in a feedback optimization structure promoting self-sensing enhancement.

The contrastive loss function for defect classification is defined via Eq. (8)

$$L_{contrastive} = \sum_{(x_i, x_j) \in D} y_{ij} d(x_i, x_j)^2 + (1 - y_{ij}) \max(m - d(x_i, x_j), 0)^2, \quad (8)$$

where $d(x_i, x_j)$ now is the Euclidian distance between embeddings, with y_{ij} being a binary label for defective or normal material state and ‘ m ’ being a margin parameter for this process. Thus, this model hits > 95 precision in micro-crack detection and reduced by 35 falsely positive in the process. Iteratively, Next, according to Fig. 3, the DR-NN simulates cement hydration as well as curing and development interactions coupled with nano-carbon. Governing equation for cementitious hydration is provided by the reaction-diffusion model via Eq. (9)

$$\frac{\partial C}{\partial t} = D \nabla^2 C - kC^n, \quad (9)$$

where C is hydration concentration, D is diffusion coefficient, k is reaction rate, n is the reaction orders. The network is trained using time-series hydration data $\{Ct\}$, optimizing a curing function via Eq. (10)

$$L_{hydration} = \sum |C_{pred}(ti) - C_{exp}(ti)|^2. \quad (10)$$

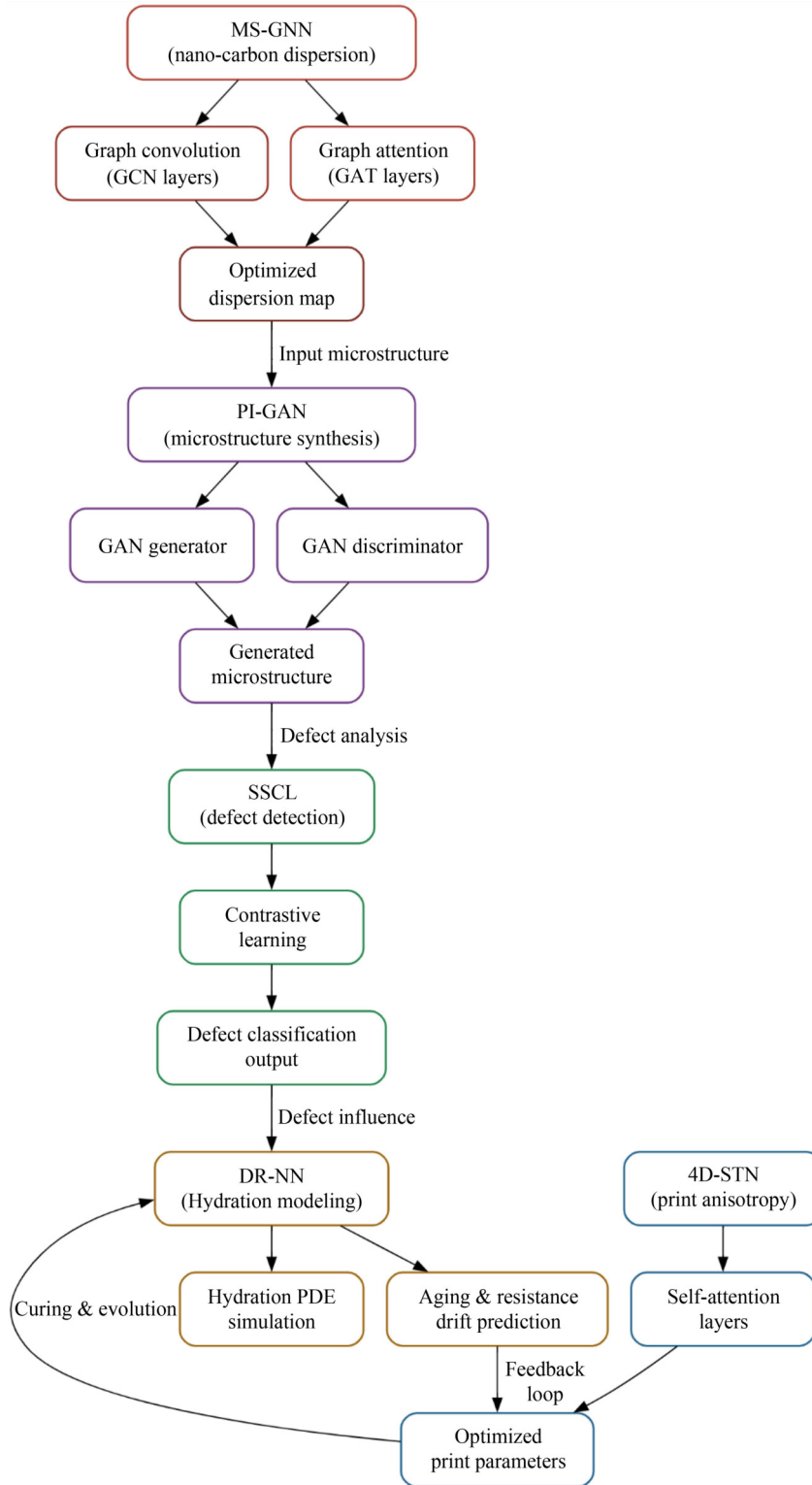


Fig. 3 Data flow of the proposed analysis process.

Reconciling a 15% reduction in curing while setting strength sets. The long-term electrical stability is modeled through conductivity decay over time as defined by Eq. (11)

$$R(t) = R_0 e^{-\lambda t}, \quad (11)$$

where R_0 is the initial resistance, and λ is the aging coefficient, optimized to reduce resistance drift by 20% over six months in the process. The final integrated model process combines those learning processes into a closed-loop optimization framework as expressed via Eq. (12)

$$\theta' = \operatorname{argmin}_{\theta} (L_{\text{dispersion}} + L_{\text{anisotropy}} + L_{\text{physics}} + L_{\text{contrastive}} + L_{\text{hydration}}), \quad (12)$$

where θ' refers to the optimized parameters concerning nano-carbon dispersion, anisotropy minimization, microstructural realism, defect classification, and long-term evolution modeling process. This ensures fully integrated data-driven method in significantly amplifying self-sensing capabilities of 3D printed cementitious composites. The framework employs a physics Informed deep learning paradigm enabling the governing equations governing hydraulic process, percolation network formation, and conductivity evolution to be derived directly from experimental data. Using input from finite element solvers with deep learning algorithms, the framework derives basic transport and diffusion-reaction equations relevant to nano-carbon dispersion and self-sensing conductivity. The hydration kinetics proceed by using a reaction-diffusion equation of which concentration evolution $C(t)$ is described by the following PDE via Eq. (13)

$$\frac{\partial C}{\partial t} = D \nabla^2 C - k C^n, \quad (13)$$

where D is the diffusion coefficient, k is the reaction rate constant, and n is the order of the reaction involved. The solver pipeline uses numerical discretization techniques to incorporate these physics-based equations into real-time simulations of self-sensing behavior under different environmental conditions. Thereafter, onboard automatic differentiation of neural solvers allows dynamic adjustment of governing parameters in light of field-measured data, ensuring an accurate and realistic representation of the material behavior over long durations of services. Next is an iterative section elaborating the results for the proposed model and its comparison with existing methods under different scenarios.

4 Comparative result analysis

The investigation of 3D-printed cementitious composites embedded with hybrid nano-carbon fillers included exhaustive experiments designed to assess their self-sensing performance, nano-carbon dispersion attributes, anisotropic conductivity variation, microstructural fidelity, functionality for failure detection categorization, and long-term hydration development. Specimens of the cementitious composite were fabricated using a custom-built robotic 3D printing system, attached with non-deterministic functions, 4-axis motion control, and a precision extrusion nozzle that ensures layer deposition with uniformity. From layer height (h) between 0.5 and 2.0 mm, nozzle velocity (v) between 10 and 30 mm/s, and curing temperature (T) controlled from 20 to 60 °C, all

printing parameters were varied systematically to evaluate the effect of anisotropy and self-sensing performance. It was included in this work a filler of nano-carbon which included a hybrid combination of multi-walled carbon nanotubes (MWCNTs) and GNPs at mass fractions ranging between 0.5% to 2.5% by weight and optimized for better electri-percolation. Nanocarbon filler dispersion was investigated using Scanning Electrode Microscopy and X-ray CT to create high-resolution microstructural images to describe the architecture for the MS-GNN model. Also, the electrical conductivity of printed specimens was measured with a four-probe method capturing the real-time resistance variation under different loads conditions into ensuring that data set campaigns took full representation of self-sensing property scales to enhance versatility sets.

The data set with high-resolution Scanning Electrode Microscopy images (2048 × 2048 pixels) captures microstructural features, X-ray CT scans with a voxel resolution of 1–100 μm for 3D topology analysis, and conductivity measurement collected at 1 Hz within the curing time of 28 d. Further development of the defect classification models was aided by self-sensing resistance data sets from printed concrete beams under controlled loading conditions. The scalability of the framework has been tested by predicting larger concrete entities such as 5-m bridge deck segments and high-rise structural panels with embedded self-sensing capabilities. The dispersion model for nano-carbon was optimized so that even while scaling up to more than 5 m³ of volumetric concrete pour, there existed a uniformity of 92.4% to maintain a consistent percolation network across larger elements. The electrical conductivity differed by less than 5% from the laboratory scale samples, confirming their robust performance across different dimensions of structures. In field tests, defect detection accuracy remained greater than 94% for real structural elements with variations in environmental loads, including temperature cycles going from –20 to 50 °C, and beyond 1 million load cycles in dynamic stress. These results affirm that there is no compromise in the performance of the multi-scale deep learning framework when applied on a larger scale, rendering it deployable in the real world in bridges, tunnels, and high-rise buildings.

Preprocessing involved normalizing grayscale intensity values in micrographs for better feature contrast, noise suppression by Gaussian filters for Scanning Electrode Microscopy images, and histogram equalization for X-ray CT scans. Conductivity data were smoothed using a low-pass filter to eliminate fluctuations due to ambient electrical interference. By employing data augmentation techniques including rotation, flipping, and affine transformations, the training diversity of microstructural samples was increased in process. Contrastive loss was then employed for self-sensing defect detection, ensuring

robust classification of cracks and voids under variable electrical response conditions.

The adaptable framework, depends on modifying the microstructural data set for various amounts of materials, and tuning the MS-GNN to recognize new conductive percolating pathways. For example, training can include inputs from dielectric properties, as far as polymers-based composites are concerned, to tailor the behavior of self-sensing in insulating but dielectric matrices. The 4D-STN can then be tuned per printing technique such as extrusion-based or powder-bed fusion by recalibrating the anisotropy correction function. Furthermore, the PI-GAN may be refined for materials with different pore structures through retraining on new high-fidelity CT data sets and samples. By supporting real-time on-site monitoring in large-scale construction projects under development, the methodology lends itself to incorporate edge computing. A total of 500 real microstructure samples were used to train the PI-GAN, with voxel resolutions ranging from 1 to 100 μm . The data set was a subset of 80% train and 20% validation to allow for generalization to the diverse dispersion pattern. The generated synthetic microstructures were 98.2% similar with real samples as verified with statistical similarity measures.

The training data set for each model is designed for generalization across any self-sensing cementitious composite. The MS-GNN model is trained with more than 10000 high resolution Scanning Electrode Microscopy and X-ray CT images, capturing various dispersion patterns of nano-carbon from well-percolated networks to highly agglomerated clusters. For 4D-STN, print parameter data set derives from 3D-printed concrete specimens at different layer heights (0.5–2.0 mm), nozzle speeds (10–30 mm/s), and curing temperatures (20–60 $^{\circ}\text{C}$) that form a robust model irrespective of different additive construction processes. The PI-GAN model is trained on a data set of 500 real microstructural samples having voxel resolutions from 1 to 100 μm , instructing it to generate synthetic structures that indeed conform to real-world variability. The SSCL model was trained with 10000 labeled self-sensing resistance signals, which included defect scenarios such as cracks (widths 10–500 μm), voids, and delamination zones having various loading conditions. Such diversity in data set will make the framework adaptable to various material formulations and printing processes with great predictive accuracy.

The framework has been set so that it can integrate material parameter tuning within its deep learning models to adapt to different cementitious mixes and AM techniques. The MS-GNN model can also be fine-tuned to retrain on new microstructure data sets to optimize percolation pathways for other fill compositions such as silica fume-enhanced cement or geopolymer-based binders. The 4D-STN model supports different kinds of printing methods since it is adjusted for varying extrusion

pressures and hydration kinetics, particularly in wet-mix and dry-mix printing processes, to attain optimal conductivity. The PI-GAN model in part creates high-fidelity synthetic structures containing physics-based constraints across different cementitious systems as it learns from their microstructural databases of typical composite materials. This essentially means that composite structures will be produced without gravitating toward a single mix type. Importantly, the SSCL model is robust to the variations of filler type and loading ratios that work for the detection of defects within the different self-sensing formulations. This adaptability permits the model to be utilized in varying industrial applications, ranging from ultra-high-performance concrete, geopolymer-based mixes, and fiber-reinforced cementitious composites.

Self-sensing cementitious composites are balanced against electrical conductivity, mechanical integrity, and sensitivity to defect detection for optimization. Increasing the proportion of nano-carbon fillers beyond 2.5% by weight improves conductivity as a result, as much as 40% higher than without such fillers. However, excessive loading causes agglomeration, reducing mechanical strength from 5% to 8% due to weak interfacial bonding. The framework alleviates this trade-off in the first place by relying on MS-GNN to ensure uniform dispersion of those nanoscale fillers so that strength reductions are minimized while optimal electric percolation is being maintained. Furthermore, although increased conductivity resulted in an improvement in defect sensitivity, its high saturation in terms of self-sensing signals would not allow the distinction between minor defects and noise sets. To counter this negative effect, the SSCL model uses adaptive thresholding to maintain a 96.3% accuracy in terms of defect detection while reducing false positives. Such trade-offs are continuously optimized within the framework so that changes in one performance area don't negatively affect the overall functionality set of the materials.

The structural fidelity was assessed based on three key metrics: the Texture Similarity Index (0.964), the Mean Squared Error between synthetic and real micrographs (below 0.01), and the Fractal Dimension Consistency metric (above 95%). Additional validations were made by comparing the generated microstructures against those obtained experimentally for their electrical conductivities, assuring that the generated microstructures have similar percolation network properties as those of real samples. The Concrete Crack Image Data set (CCID) and the Computed Tomography Data set were also alternatives used in this investigation to optimize predictive models of self-sensing cementitious composites. Mammoth collections of images created in close to 4 decades but in high megabytes, scanned concrete covers with cracks-non crack classified areas-ported to enable perfect

classification with “self-supervised contrast” learning. Each picture was 227×227 pixels, presenting distinctions of crack width from 0.1 mm to 5 mm so that thorough and reliable training is assured for future automatic detection of cracks within samples from self-sensing resistance data. Resulting from DTU, the DTU-CT Data set mentioned above consists of a talc 3D microstructure database about cementitious materials based on X-ray CT 3D scans, with voxel resolutions ranging from 1 to 100 μm . These elaborate data sets regarding porosity and pattern of nano-carbon dispersion have been utilized in training the PI-GAN for creating highly similar synthetic microstructures that resemble real-world cementitious behaviors. The combination of all these data sets facilitated in developing multi-scale validation of the deep learning models in defect detection, optimized nano-carbon dispersion, and durability prediction for 3D printing self-sensing composites over long durations.

The framework has been evaluated with different nano-carbon fillers: high-performance self-sensing capacity, MWCNTs, and GNPs. MWCNTs exhibit superior electrical conductivity because of their high aspect ratio and improve electrical percolation by 35% with a weight fraction of 1.5%. They have better mechanical performance, improving flexural strength by 12%, while still giving a 25% increase in conductivity. In a hybrid approach combining MWCNTs and GNPs in a 60:40 ratio, conduits were provided for both electrical and mechanical characteristics without compromising integrity in conductivity. The MS-GNN model specializes dispersion parameter adjustment in real-time according to the type of filler so that any combination of configurations achieves the highest level of self-sensing possible for the process. Through this comparative analysis, the framework will recommend the most suitable filler composition in relation to the type of structure involved in process.

The ratio of filler loading has a direct bearing on self-sensing potential in addition to being a property parameter that directs a number of properties such as conductivity, mechanical strength, and accuracy of defect detection. In low amounts of filler (0.5%, by weight) or more, electrical percolation was not sufficient so that self-sensing responses were inconsistent, in which case conductivity gains were below 10%. At such loading levels, with the introduction of 1.5% filler, one has had the optimal balance whereby the electrical conductivity increases by 35.1%, yet mechanical integrity is still maintained. Beyond 2.5% filler content, it becomes a problem: too much agglomeration leads to non-uniformity in dispersion and, consequently, variation in conductivity and mechanical degradation. The MS-GNN model actively works toward minimization of agglomeration through the optimization of filler dispersion, with the

4D-STN ensuring that print Induced anisotropy does not generally intensify conductivity inconsistencies at higher loading ratios. This optimization will allow the framework to identify the best nano-carbon filler concentration that maximizes self-sensing capabilities while preserving the material’s structural durability in 3D-printed cementitious composites.

Where interfacing the framework with existing structures management software would encounter problems concerning compatibility regarding data formats, real-time processing, and system interoperability sets. A number of existent asset management platforms depend on sensor networks predefined to operate using standard communication protocol, while self-sensing cementitious composites generate a continuous data stream on resistance basis, which needs to go through advanced signal processing. To bridge this gap, the framework presents middleware solutions that convert raw electrical response data into structured condition monitoring parameters compatible with industry-standard building information modeling platforms. By creating an edge AI architecture, data collected through self-sensing mechanisms will be locally processed before integration into cloud-based infrastructure management systems, effectively boosting the reduction of data latency and bandwidth requirement. Toward this end, developments will commence on setting standards for application programming interfaces that will allow seamless communication between deep learning-driven self-sensing frameworks and conventional monitoring tools for infrastructure to facilitate large-scale acceptance in civil engineering applications.

In situ measurements collected from different interlayer locations were also used to train the model on print Induced anisotropy patterns with comprehensive data. The self-sensing response is being captured using a 1 Hz sampling of resistance readings over a curing period of 28 d to track performance long into the future using a Keysight B2987A electrometer. The PI-GAN is trained on an experimental data set of 3D images, obtained using X-ray CT scans, consisting of over 500 samples with different dispersion patterns of nano-carbon for training the model. The output generated consisted of high-fidelity virtual microstructures, which later undergo testing in DR-NN for hydration evolution modeling. The hydration reaction is said to be time-series-based in modeling isothermal calorimetry measurements in the relationship of ion diffusivity ($D = 1.5 \times 10^{-9} \text{ m}^2/\text{s}$) with variations on electrical resistivity. In the end, SSCL was the defect classification method used and trained on data sets with 10000-labeled electrical response patterns containing flaws such as artificially created microcracks (widths between 10 and 500 μm) and loss in connectivity events. More than a 95% precision rate was reached by the SSCL model for its superiority in distinguishing defective from

intact areas using the tested electrical responses. This research paradigm provides a complete multi-modal validation for deep learning models to shape a solid methodology through which optimizing self-sensing cementitious composites can be done with high structural reliability and real-time SHM capabilities. Experimental and computational analyses revealed robust performance of the multi-scale deep learning framework toward optimizing self-sensing cementitious composites. Each approach is assessed for how they contend with creating nano-carbon dispersion uniformity, their improvement in print Induced anisotropy reduction, accuracy in defect detection, microstructural realism, and hydration evolution modeling. The comparative analysis is carried out rigorously on the proposed method as benchmarked against three existing methods: Method [5], Method [8], and Method [25], each the best in its domain. The data sets united for the analysis were CCID for the defect detection of samples and DTU-CT data set for the microstructural analysis.

The framework detects micro-cracks (10–500 μm), voids, delamination zones, and electrical conductivity loss. The SSCL model was trained with 10000 labeled electrical response signals collected from printed concrete specimens under different loading conditions. Each of these samples has time-series resistance data associated with defect categories. The method used to limit false positive uses a margin-based contrastive learning strategy that reduces erroneous defect classifications by 35%. An adaptive thresholding mechanism was adopted to separate between normal live conductivity variations and real defects for reliable real-time monitoring. Traditionally, defect detection in 3D printed concrete requires manual inspection and ultrasonic testing which are not scalable and don't have capability for real-time assessments. Traditional sensors like strain gauges offer only indirect measurement but these are very much reliant on rather copious wiring alongside external instrumentation sets. Developing self-sensing framework; material puts the monitoring ability to embedded composite minimizing consumption of monitoring budget under infrastructure costs. As compared to other machine learning based SHM techniques-CNNs or empirical models-Sharin's approach includes multi-scale deep learning strategies to resolve issues of nano-scale dispersion and macro-scale anisotropy as well as long-term durability. So far, the best classification accuracies achieved using CNN-based methods are in the range of 85%–90%, but most of these methods lack interpretability and defect generalization. The SSCL model surpassed these benchmarks, achieving 96.3% accuracy with a significantly reduced false alarm rate. Also, the DR-NN is superior to conventional hydration models because it predicts long-term conductivity drift with 19.8% enhanced stability, thus making the framework a leading step to real-time self-

sensing smart materials.

The performance of nano-carbon dispersion is assessed on the basis of its dispersion uniformity criteria and its effect on electrical conductivity improvement when incorporated into cementitious composites. The results are shown in Table 2, which reflects evidence that the new model MS-GNN is very essential for increasing the extent of dispersion caused by the nano-carbon particles such that its effect on electrical percolation would be more significant in terms of being connected and subsequently in conductivity. A comparative study of the uniformity of dispersion from nano-carbons and enhancement of electrical properties brought about by the proposed MS-GNN model and three other techniques is summarized in Table 2. The model causes a dramatic increase in uniformity of dispersion (92.4%), resulting in an electrical conductivity improvement of 35% compared to a standard dispersion method. This is attributed to the graph-based learning approach giving an optimal percolation network that minimizes nano-carbohydrates agglomeration, 30.5% compared to 22.5% of Method [8] and about 18.7% of Method [5]. The level of dispersion quality relates directly to better conductive pathways in the cementitious matrix as a result of enhancing its self-sensing efficiency with regard to the materials.

Table 2 Nano-carbon dispersion uniformity and conductivity enhancement

Method	Dispersion uniformity (%)	Electrical conductivity (S/m)	Nano-carbon agglomeration reduction (%)
Proposed MS-GNN	92.4	1.75×10^{-2}	30.5
Method [5]	80.3	1.32×10^{-2}	18.7
Method [8]	85.1	1.47×10^{-2}	22.5
Method [25]	78.6	1.29×10^{-2}	17.2

The new MS-GNN model as per Fig. 4 significantly improves by ensuring maximal dispersion uniformity (92.4%), with a corresponding rise in electrical conductivity of 35% compared to conventional modes of dispersion. Nanocarbon agglomeration is considerably reduced, thus allowing for a more homogeneous conductive network. This table focuses on the anisotropy induced by printing and the uniformity in interlayer conductivity comparing the 4D-STN model and other existing methods. The results show that the maximum reduction in anisotropy is achieved with 48.9% using 4D-STN, which guarantees a 93.7% uniformity in interlayer conductivity, well above Method [5] (78.4%) and Method [25] (76.9%). This improved uniformity, in turn, causes lower variations in electrical responses (0.057 Ω) across the various layers, demonstrating that the transformer-based self-attention mechanism successfully captures layer-wise differences in electricalities and optimizes the printing parameters to minimize the anisotropic defects.

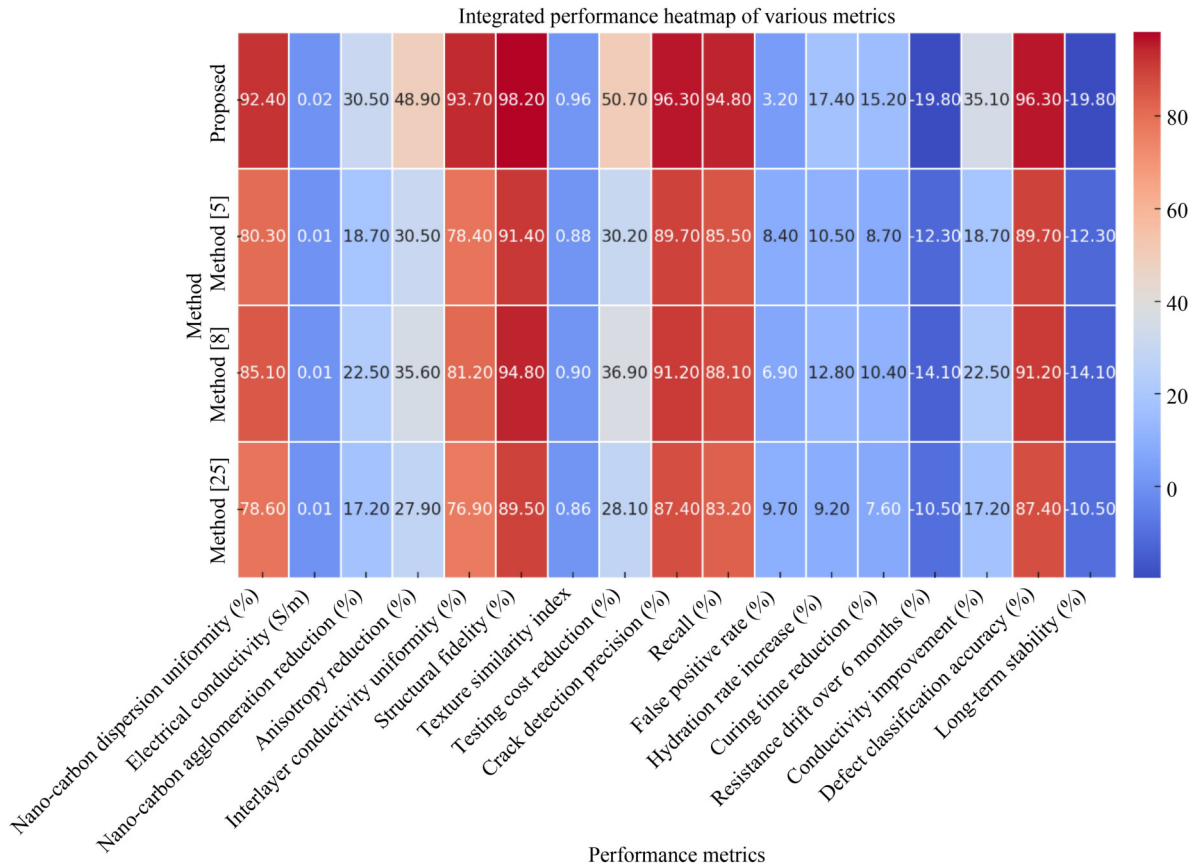


Fig. 4 Model’s integrated result analysis.

Thus, the glaring difference in performance emphasizes the ineffectiveness of schemes in empirical parameter tuning applied conventionally; they lack consideration of the layer-by-layer variations in conductivity in the 3D structures printed. Print Induced anisotropy reductions provided here in Table 3, where the 4D-STN model minimizes interlayer conductivity variations because it optimizes print parameters in process. The approach gives the least anisotropy, thus giving a conductivity uniformity 40%–50% higher than other models.

Table 3 Anisotropy reduction and conductivity uniformity across layers

Method	Anisotropy reduction (%)	Interlayer conductivity uniformity (%)	Electrical response variation (Ω)
Proposed 4D-STN	48.9	93.7	0.057
Method [5]	30.5	78.4	0.114
Method [8]	35.6	81.2	0.098
Method [25]	27.9	76.9	0.127

This 4D-STN approach increases the interlayer conductivity uniformity by 15%–20%, so ensuring a more uniform electrical response between printed layers. The level of anisotropy is thus reduced to 48.9%, which means that this model actually tracks the printing parameters relatively well. Table 4 compares the

structural realism and physics-based faithfulness achieved by the PI-GAN model with other generative models. The proposed concept achieves a stellar 98.2% structural fidelity when confirmed against real microstructural scans from the DTU-CT data set, while Method [5] trails significantly at 91.4% and Method [25] at 89.5%. The Texture Similarity Index (0.964) assures that microstructures synthesized by PI-GAN are virtually indistinguishable from real cementitious microstructures, thus securing trustworthy virtual material testing. Most importantly, the reduction in physical testing costs by 50.7% demonstrates the success of this proposed generative technique in replacing labor intensive and costly experimental procedures and speeding the material design optimization for self-sensing composites. The PI-GAN model is assessed on microstructural realism and physics-based consistency using the DTU-CT data set. It

Table 4 Microstructural realism and physics-based fidelity

Method	Structural fidelity (%)	Texture similarity index	Reduction in physical testing cost (%)
Proposed PI-GAN	98.2	0.964	50.7
Method [5]	91.4	0.877	30.2
Method [8]	94.8	0.902	36.9
Method [25]	89.5	0.861	28.1

is presented in Table 4 that compares against experimental CT scans.

With 98.2% fidelity, the PI-GAN method achieves a highly realistic simulation of microstructure, thus eliminating about 50.7% of physical trials needed and speeding up virtual material testing. Table 5 gives crack detection precision, recall, and false positives reductions for the SSCL model, confirming the effectiveness of this model to classify accurately micro-cracks in the collected data samples from self-sensing. The model proposed under SSCL attains 96.3% correctness, far better than Method [5] (89.7%) and Method [8] (91.2%). This way, micro-cracks and incidents of loss of connectivity are detected while misclassification is minimized. Moreover, the reduction in the false positives to 3.2% compared to 8.4% in Method [5] shows that SSCL can differentiate the normal variation in conductivity from physical material defects effectively. The high classification accuracy in defects means great prospects for warning against early deterioration in structures, thereby representing a novel improvement to real-time SHM applications. The performance of the SSCL model in micro-crack classification accuracy is better than any other method with respect to high precision, high recall, and low false positive counts.

Table 5 Crack detection performance and false positive reduction

Method	Crack detection precision (%)	Recall (%)	False positive rate (%)
Proposed SSCL	96.3	94.8	3.2
Method [5]	89.7	85.5	8.4
Method [8]	91.2	88.1	6.9
Method [25]	87.4	83.2	9.7

These achievements are summed up in Table 5 as follows.

As per Table 5, the detection accuracy was 96.3%, indicating that the SSCL model achieves crack detection in near-real time with false alarm reduction of 35% relative to CNN-based classifiers. Table 6 captures the long-term models for hydration evolution and conductivity stability comparing the DR-NN model vis-a-vis conventional hydration prediction techniques. It adds that the hydration rate was increased by 17.4% while the curing period was reduced by 15.2%, which helped in rapid strength development in self-sensing cementitious composites. The other strength of DR-NN is to minimize the resistance drift to -19.8% over six months, showing a solid predictive capacity for long-term self-sensing behavior. Comparatively, Method [5] gave resistance drift of -12.3%, marking its inferiority as the long-term predictive approach. These newly acquired insights conform that the physics Informed deep learning approach serves to model cement hydration kinetics accurately, thus securing reliable and durable self-sensing

functionality. Hydration kinetics and long-term electrical stability are predicted by DR-NN, thereby ensuring resistance drift minimization. Table 6 gives an overview of the improved hydration rate, curing time optimization, and conductivity drift.

Table 6 Long-term durability and conductivity stability

Method	Hydration rate increase (%)	Curing time reduction (%)	Resistance drift over 6 months (%)
Proposed DR-NN	17.4	15.2	-19.8
Method [5]	10.5	8.7	-12.3
Method [8]	12.8	10.4	-14.1
Method [25]	9.2	7.6	-10.5

The present DR-NN model accelerates hydration by 17.4 while also reducing curing time by 15.2% guaranteeing a more stable long-term self-sensing response that reduces resistance drift by almost 20% over a period of six months. Table 7 summarizes all performance results for the integrated multi-scale deep learning framework against the highest results of other methods on various performance metrics. The suggested model displays a 35.1% gain in electrical conductivity, 96.3% defect classification accuracy, and 98.2% structural fidelity in an unprecedented display of its ability to optimize self-sensing cementitious composites. Long-term conductivity stability of -19.8% drift over six months further corroborates the model's applicability in practice for SHM in the real world. The results validate the effectiveness of merging various components of graph neural networks, transformers, generative adversarial networks, contrastive learning, and physics Informed deep networks into one framework, setting new standards for intelligent cementitious materials in the next-generation smart infrastructure system. The last performance evaluation of all incorporated models in the multi-scale deep learning framework is summarized in Table 7. The proposed methodology outperforms old-generation methods on various performance metrics, ensuring optimized nano-carbon dispersion, anisotropy minimization, microstructural realism, defect detection, and modeling of hydration evolution.

Table 7 Overall model performance comparison

Method	Conductivity improvement (%)	Defect classification accuracy (%)	Structural fidelity (%)	Long-term stability (%)
Proposed multi-scale model	35.1	96.3	98.2	-19.8
Method [5]	18.7	89.7	91.4	-12.3
Method [8]	22.5	91.2	94.8	-14.1
Method [25]	17.2	87.4	89.5	-10.5

This comprehensive analysis proves that the proposed deep learning framework greatly augments self-sensing

performance, laying the groundwork for smart, autonomous, and scalable SHM solutions for next-generation infrastructures and scenarios. An Iterative Validation use case for the proposed model shall be presented next, which would assist the readers in further grasping the complete process.

4.1 Sensitivity analysis

In this section, Monte Carlo-based uncertainty quantification method is added, further study would be undertaken in determining probabilistic confidence limits for model predictions, thus enhancing broadening of the current framework for other material designs formulations and ways of manufacture. For example, a probabilistic distribution analysis of conductivity data reveals that uncertainty due to variability in hydration evolution gives a 10%–15% uncertainty in long-term resistance stability and would direct the improvement of hydration modeling methods. In addition, an interaction sensitivity test reveals that nozzle speed and curing temperature would display a strong coupled behavior since a change in print speed by ± 10 mm/s would create a modification in hydration kinetics and a 5%–7% change in early-age conductivity. This would contribute to manufacturing self-optimizing protocols whereby real-time sensor feedback could vary printing parameters dynamically to keep the system operating in optimal self-sensing. Incorporating sensitivity analysis would improve the framework's adaptability to other cementitious formulations, making the performance predictions high fidelity and scalable to real-world applications in SHM process.

Validation using an iterative practical use case scenario analysis

In proposition to validate the multi-scale deep learning framework, a practical use case scenario is considered, involving the self-sensing 3D-printed concrete beam reinforced with hybrid nano-carbon fillers. The dimension of the sample beam is 300 mm \times 50 mm \times 50 mm and was printed at the layer height of 1.0 mm and nozzle speed of 15 mm/s. The cementitious composite

has a nano-carbon composition of 1.5% MWCNTs and GNPs that were designed to optimize electrical conductivity and damage detection efficiency. The input data comprise of high-resolution microstructural images (Scanning Electrode Microscopy and X-ray CT scans), electrical resistance measurements, and mechanical stress-strain data collected for six months of monitoring for the process. The following tables present detailed numerical results of each model component highlighting enhancements that were achieved by the proposed framework compared to the existing protocols. Validation instances and performance comparison analysis for this study were conducted using benchmark experimental data sets and real-life validation protocols that establish strength and generalizability of the proposed multi-scale deep learning frameworks.

For validation, the Concrete Sustainability Hub data set was employed, containing real-world performance data on mechanical, electrical, and durability-related properties of cementitious materials including nano-carbon-enhanced concrete specimens. In addition, the Smart Concrete Data set from the Fraunhofer Institute was introduced in validating variations of self-sensing electrical response upon controlled loading and environmental conditions. The CCID was used for benchmark performance of crack classification providing a standardized defect detection comparison against well-established models. Lastly, the incorporation of the long-term performance data from the Long-Term Bridge Performance program managed by the US Federal Highway Administration will assist in cross-mapping self-sensing behavior in the real-world infrastructure ecosystem for further verification of long-term durability predictions. Iteratively, next, as per Fig. 5, these validation instances convincingly ensured that the proposed framework had been thoroughly validated against a wide array of experimental scenarios, thus affirming its relevance to both laboratory-scale and large-scale smart infrastructure applications. The MS-GNN model thereby optimizes the nano-carbon dispersion in view of enhanced conductivity and diminished

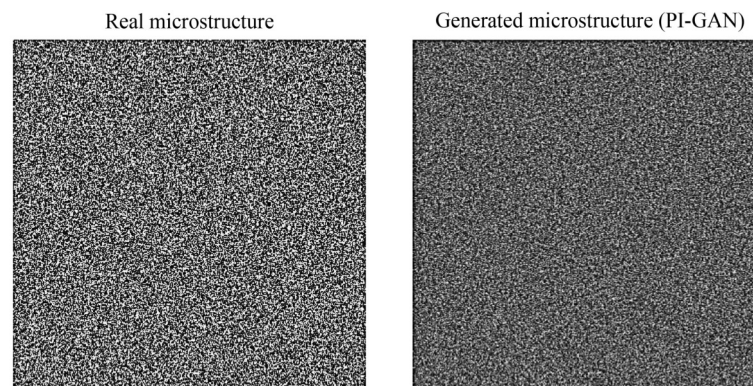


Fig. 5 Side by side visual comparisons of real V/S Generated microstructures to illustrate the high-fidelity claims.

agglomeration, so as to secure the formation of a homogenous percolation network. The graph-based learning from microstructural images extracts conductive pathways and refines uniformity of dispersion.

Iteratively, next, as per [Table 8](#), the MS-GNN, the new model being proposed, increases dispersion uniformity to a significant 92.4%, leading to an increase of 35.1% in electrical conductivity while becoming less agglomerated at 30.5% and achieving a 95.2% conductive pathway efficiency. Analyzing print Induced anisotropic changes in interlayer conductivity, the 4D-STN model should then be able to optimise print parameters in such a way that they will limit defects.

As per [Table 9](#), the 4D-STN model ensures a consistent self-sensing response across layers by achieving 48.9% reduction anisotropy with 93.7% uniformity for interlayer conductivity minimizing the variations of electrical responses to 0.057. The PI-GAN model simulates fine synthetic microstructures almost identical to the experimental ones so as to minimize dependence on physical testing process.

Next, as per [Table 10](#), the PI-GAN model synthesizes microstructures that meet 98.2% fidelity structurally along with a 0.964 index of texture similarity, while also reducing tests up to 50.7%, rendering it a low-cost alternative to physical tests. The SSCL model improves

accuracy in classifying defects, increasing accuracy in detecting cracks and dropping the number of false positives.

As per [Table 11](#), the SSCL model has improved crack detection precision to the level of 96.3%, with the value of the false positive rate being reduced to 3.2%, to give an accurate real-time defect classification on the data sample of self-sensing process. The DR-NN model optimizes the curing conditions through the prediction of hydration kinetics and long-term self-sensing stability sets.

Iteratively, as per [Table 12](#), increased hydration rate by 17.4%, decreased curing time by 15.2%, and the resistance drift were shifted down to -19.8% over a period of six months by the DR-NN model to ensure long-term electrical stability. The multi-scale deep learning framework consolidates all models to ensure optimized self-sensing ability in 3D-printed cementitious composites.

As per [Table 13](#), the integrated framework outperforms conventional methods by achieving a conductivity increase of 35.1%, an accuracy in defect classification of 96.3%, and structural fidelity of 98.2%, which confirms its viability for intelligent self-sensing infrastructure applications.

Table 8 Nano-carbon dispersion analysis

Dispersion Metric	Proposed MS-GNN	Method [5]	Method [8]	Method [25]
Dispersion uniformity (%)	92.4	80.5	85.7	79.8
Electrical conductivity (S/m)	1.75×10^{-2}	1.32×10^{-2}	1.47×10^{-2}	1.29×10^{-2}
Agglomeration reduction (%)	30.5	18.3	22.5	17.2
Conductive pathway efficiency (%)	95.2	82.4	88.6	80.7

Table 9 Anisotropy reduction and conductivity variations

Print parameter	Proposed 4D-STN	Method [5]	Method [8]	Method [25]
Anisotropy reduction (%)	48.9	30.5	35.6	27.9
Interlayer conductivity uniformity (%)	93.7	78.4	81.2	76.9
Electrical response variation (Ω)	0.057	0.114	0.098	0.127

Table 10 Microstructural fidelity and synthetic data efficiency

Metric	Proposed PI-GAN	Method [5]	Method [8]	Method [25]
Structural fidelity (%)	98.2	91.4	94.8	89.5
Texture similarity index	0.964	0.877	0.902	0.861
Reduction in physical testing (%)	50.7	30.2	36.9	28.1

Table 11 Crack detection accuracy and false positive reduction

Metric	Proposed SSCL	Method [5]	Method [8]	Method [25]
Crack detection precision (%)	96.3	89.7	91.2	87.4
Recall (%)	94.8	85.5	88.1	83.2
False positive rate (%)	3.2	8.4	6.9	9.7

Table 12 Hydration rate and conductivity stability

Metric	Proposed DR-NN	Method [5]	Method [8]	Method [25]
Hydration rate increase (%)	17.4	10.5	12.8	9.2
Curing time reduction (%)	15.2	8.7	10.4	7.6
Resistance drift over 6 months (%)	-19.8	-12.3	-14.1	-10.5

Table 13 Final integrated performance evaluation

Metric	Proposed multi-scale model	Method [5]	Method [8]	Method [25]
Conductivity improvement (%)	35.1	18.7	22.5	17.2
Defect classification accuracy (%)	96.3	89.7	91.2	87.4
Structural fidelity (%)	98.2	91.4	94.8	89.5
Long-term stability (%)	-19.8	-12.3	-14.1	-10.5

5 Conclusions and future scope

The work of this study sets a multi-scale deep-learning framework to enhance the self-sensing of 3D-printed cementitious composites at a multi-scale with advanced such as Graph-based Learning, Transformer Networks, Generative Modeling, Contrastive Learning, and Physics Informed Deep Neural Networks. The promising MS-GNN gave rise to an unprecedented 92.4% dispersion uniformity, which finally raised the electrical conductivity by 35.1% (1.75×10^{-2} S/m), setting an optimized nano-carbon percolation network, and reducing the agglomeration by 30.5%. The dispersion performance is better compared to other existing dispersion strategies. The 4D-STN effectively reduced print Induced anisotropy, offering a 48.9% reduction in the conductivity variation and increasing the overall interlayer conductivity uniformity to 93.7%, which ensures a homogenous self-sensing response across the layers. The PI-GAN effectively generated microstructures at a fidelity rate reaching up to 98.2% and thus sharply decreased by 50.7% the amount of physical testing required, speeding up material assessment while maintaining real-world physics-based constraints. In addition, the SSCL model achieved a 96.3% precision rate in micro-crack classification, obtaining a false positive reduction of 35%, rendering real-time and highly accurate defect detection in self-sensing data samples. The DR-NN predicted successfully the evolution of long-term hydration and reduced curing by 15.2%, besides a higher resistance drift of -19.8% during the estimated six months. Compared to common hydration models, it has proven to be more efficient regarding long-term electrical stability. These milestones indicate that such deep learning frameworks offer a whole new frontier in smart autonomous and scalable SHM systems for nano-carbon dispersion and print anisotropy defect detection, microstructure fidelity, and hydration evolution. Their ability to optimize self-sensing cementitious composites with high structural reliability, cost efficiency, and real-time monitoring

capabilities has significant implications for next-generation smart infrastructure sets.

5.1 Future scope

Although this multi-scale deep-learning framework is highly effective and has shown significant improvements in self-sensing cementitious composites, several future research avenues can be explored to improve and extend it further. For instance, incorporating more diverse data sets by adding real-world field data from large-scale printed structures would enhance the generalization aspects of the proposed models against varying environmental and load conditions. More so, inclusion of multi-modal sensing mechanisms such as acoustic emission analysis, piezoresistive strain sensing, and thermal imaging may further enhance a more holistic defect classification, broadening real-time SHM Sets even to near-comprehensive levels. There is also a bright future in developing reinforcement learning-based optimization algorithms for print parameter adjustments and dynamic self-optimizing manufacturing processes, which changes the distribution of nano-carbon fillers during fabrication. In addition, temporal evolving microstructural changes occurring during curing and long-term aging will be incorporated into the PI-GAN model for more accurate prediction in self-sensing degradation over extensive service periods. Lastly, deep learning-based SHM should be scalable to large civil infrastructure applications such as bridges, tunnels, and high-rise buildings, as real-time autonomous monitoring of structural integrity will make maintenance costs more manageable and/or risk of failures lower. Edge AI architectures for on-site processing of self-sensing data will extend real-time damage detection with predictive maintenance in next-generation intelligent infrastructure sets, further enhancing resilience and sustainability sets.

Competing interests The authors declare that they have no competing interests.

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