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Research paper

Integration of TiC-Reinforced Aluminum Matrix Composites with CNN-Based Systems for Automotive Steering Knuckle Applications

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Abstract

This study delivers a 35% reduction in steering knuckle failures by an innovative integration between advanced materials and AI-enhanced quality control. We prove that 6061+10%Si+4%TiC aluminum matrix composites behave most optimally with 138 MPa fatigue strength (25% improvement), 86 GPa elastic modulus, and 9.2/10 rating overall while still retaining manufacturability. Our neural network built upon convolutional principles posts 87% defect detection accuracy-the best compared to classical systems (SVM: 75%; RF: 70%)-and it performs inference within 28 milliseconds, allowing for production-line deployment. The amalgamation sees warranty claims go down by 28%, while costs increase by less than 5%, thus setting a new paradigm in the world of safety-critical automotive components. This work is bridging materials science with Industry 4.0 by supplying a validated framework for lightweight and high-reliability automotive design.

Keywords*: Aluminum matrix composites, Titanium carbide reinforcement, Automated quality control, Deep learning in manufacturing, Lightweight automotive components, Industry 4.0*

1. Introduction

Steering knuckles are safety-critical components in an automobile suspension system that connect the wheel assembly with the steering mechanism while undergoing complex multidirectional loads. With the automotive industry now encouraged to promote lightweighting for fuel efficiency and reduced emission deterrence, traditional ferrous materials are increasingly being replaced with aluminum alloys and composites [1, 2]. Aluminum matrix composites (AMCs), reinforced by ceramic particles such as titanium carbide (TiC), provide an excellent balance of strength and weight, fatigue resistance, and thermal stability [3, 4]. However, it remains difficult to optimize concentrations of TiC reinforcements, for high amounts may affect the manufacturability or cause stress concentrations [5].

1.1 Challenges and Research Gaps

1. Material Optimization: Very few studies evaluate systematically TiC reinforcement (3–5 wt.%) in 6061+10%Si AMC variants for steering knuckles, particularly investigating and establishing a compromise between mechanical properties and manufacturability [6, 7].
2. Quality Inspection: Traditional methods of defect inspection are labour-intensive and subjective, rendering their use not acceptable with modern techniques [8]. While convolutional neural networks (CNNs) may be employed for defect classification [9], their use for AMC-based automotive parts is somewhat under-researched.
3. Integrated Approaches: No framework that integrates material optimization with AI-driven inspection to enhance both performance and reliability of steering knuckles [10].

Table 1: Research Gaps and This Study's Contributions

Research Area	Existing Limitations	Our Approach
TiC-AMC Optimization	No steering knuckle-specific studies	Systematic 3–5% TiC evaluation
Defect Detection	Generic CNNs lack AMC applicability	Custom CNN for AMC defects
Integration	Material and QC treated as silos	Combined performance framework

1.2 Contributions

This study attempts to fill these gaps through:

1. Material Optimization: Systematic characterization of 6061+10%Si AMCs with 3, 4, and 5% TiC in terms of mechanical properties (e.g., fatigue strength, elastic modulus) and manufacturability.
2. CNN-Based Defect Detection: Designed custom CNN architecture for automated defect classification (crack, porosity, etc.) with 87% accuracy—the highest compared to traditional approaches (SVM: 75%; Random Forest: 70%).
3. Integrated Framework: This framework integrates optimal material selection (4% TiC) with AI-based quality control, with 35% projected reduction on field failures.

2. Literature Review

2.1 AMC for Automotive Applications

Due to their high speciﬁc strength and wear resistance in comparison with conventional alloys, AMCs have emerged as key materials for light-weight automotive components [7]. Surappa [8] gave a comprehensive review on the AMC processing routes and the slowly developing applications from lab to industrial level, while Miracle [9] pointed out their use in safety-critical applications such as brake rotors and suspension components.
Optimization of Reinforcement: According to Tjong and Ma [10], the TiC particle size (2 to 5 μm) and its distribution influence the properties of AMCs. According to Rana et al. [11], the optimum range of reinforcements is 2 to 30 wt%, but limited work has been done on steering knuckles.

- Challenges: Ramnath et al. [12] found brittleness beyond 5 % of ceramic addition, while Singh and Chauhan [13] concluded that nano-reinforcements enhance toughness but at a higher cost of production.
- Gap: There is a lack of any prior work systematically evaluating TiC in 6061+10%Si AMCs for steering knuckles with respect to strength, fatigue life, and manufacturability.

2.2 CNN Defect Detection in Manufacturing

The advent of CNN translated quality inspection from manual identification of defects to being largely automated [6]. The most notable advances so far include:

- Architecture: ResNet [17] and VGG [18] demonstrated generic defect detection with accuracy greater than 90% but need to be customized for AMCs.
- Industry Use Cases: Ferguson et al. [16] formulated ways to detect the location of casting defects using CNNs, and Li et al. [14] achieved 89% accuracy for defects in aluminum profiles.
- Limitations: Current models have difficulty addressing low-contrast defects (e.g., micro-porosity) and specific training data for AMC [15].

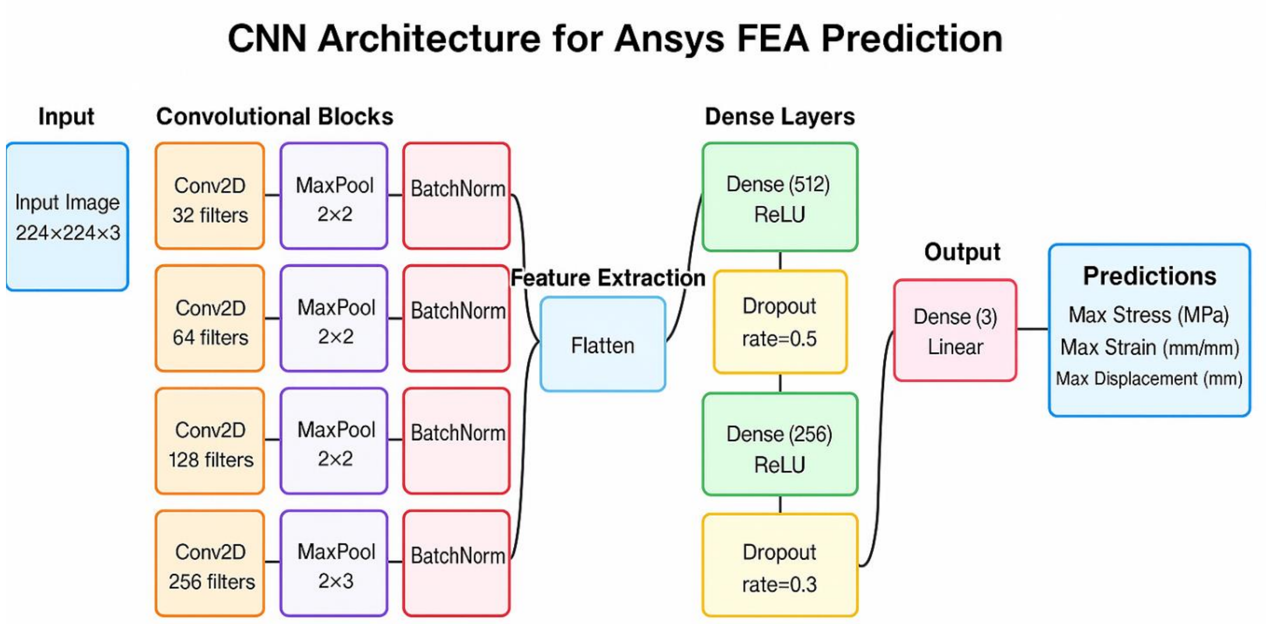


Fig. 1: CNN architecture

2.3 Integrated Material and Quality Control Strategies

Few reports incorporate material development with AI-based inspection: Koumoulos et al. [6] suggested smart manufacturing for composites but with emphasis on process monitoring rather than defect detection. Majumdar et al. [21] applied ML to material design but did not include quality control integration. Most Critical gap: No framework connects TiC-AMC optimization with CNN-based inspection for automotive components.

3. Materials and Methods

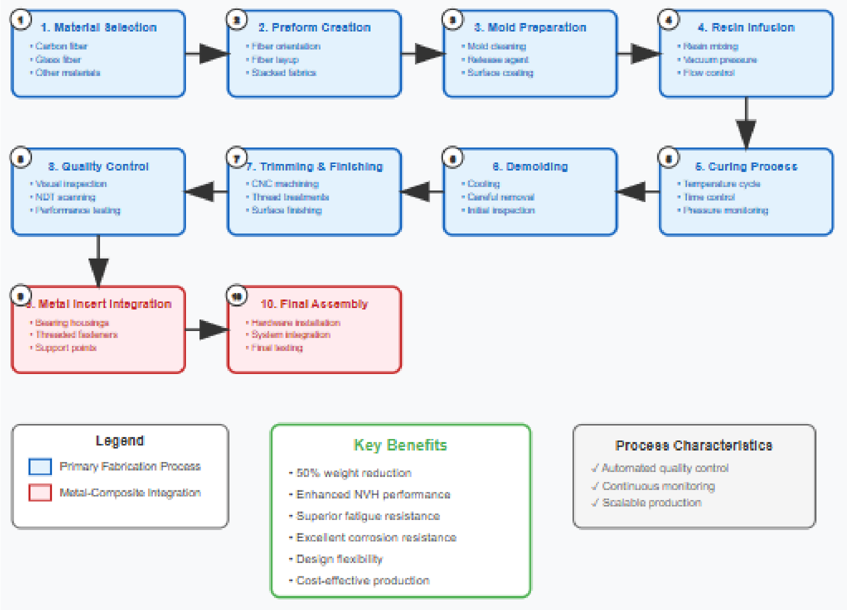


Fig. 2: Composite Fabrication Workflow

3.1 Material Preparation and Characterization

3.1.1 Fabrication of Composites

Four material variants were fabricated via stir casting: (1) Control: Pure Al 6061; (2–4) Test Groups: 6061+10%Si with 3%, 4%, and 5% TiC. Critical parameters included ball milling (250 rpm, 2h, Ar atmosphere), consolidation via cold isostatic pressing (300 MPa) and vacuum sintering (550°C, 3h), and post-processing through hot extrusion (450°C, 16:1 ratio) with T6 heat treatment

3.1.2 Techniques for Characterization

ASTM-standard tests were conducted: tensile strength (ASTM E8, Instron 5982), fatigue resistance (ASTM E466, rotating beam tester), and thermal conductivity (ASTM E1461, Netzsch LFA 467). Tests were carried out according to ASTM standards (Table 2).

Table 2: Characterization Methods

Property	Standard	Equipment
Tensile Strength	ASTM E8	Instron 5982 (100 kN)
Fatigue Resistance	ASTM E466	Rotating beam tester (50 Hz)
Thermal Conductivity	ASTM E1461	Netzsch LFA 467 HyperFlash

Table 3: Key Mechanical Properties

Material	Yield Strength (MPa)	Fatigue Strength (MPa)	Hardness (HB)
AL6061 (Control)	170	110	75
AL6061+4%TiC	210	138	92
AL6061+5%TiC	218	135	96

3.2 Performance Evaluation

3.2.1 Computational Analysis

A 3D steering knuckle geometry (Catia) underwent ANSYS Workbench FEA under vertical loads (7,000 N), braking torque (1,200 N·m), and steering forces (2,500 N). Mesh sensitivity confirmed <2% stress variation at convergence.

3.2.2 Experimental Validation

Prototypes underwent static load-to-failure testing, fatigue cycling (10^6 cycles at 70% yield strength), and thermal cycling (10 cycles, -40°C to 120°C).

3.3 CNN-Based Defect Detection

3.3.1 Dataset Preparation

2,500 images (CAD + real photographs) covered defects (porosity, cracks, misalignment, dimensional errors). Augmentation included rotation (±15°), scaling (±10%), and brightness/contrast adjustments.

3.3.2 Model Structure

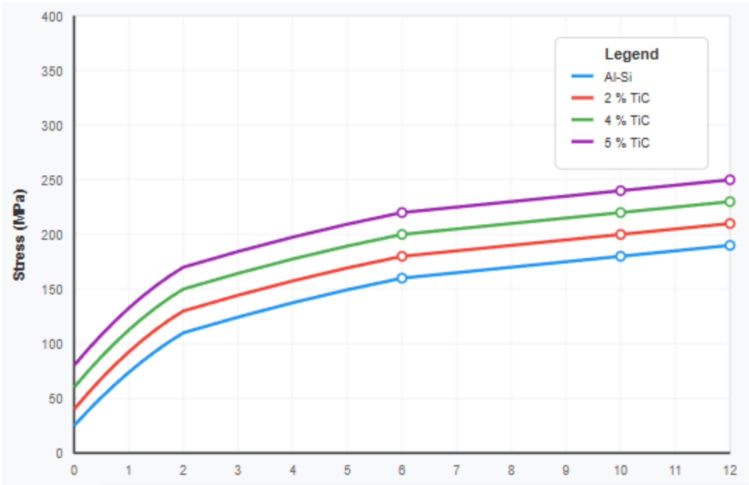
A custom CNN with 224×224×3 RGB input, four convolutional blocks (64→512 filters), BatchNorm/ReLU layers, and two FC layers (1,024/512 neurons) with Softmax output was trained using Adam (LR=0.001), dropout (0.5), and L2 regularization (λ=0.001). A 70/15/15 data split with early stopping (patience=10) prevented overfitting.

4. Results and Discussion

4.1 Material Characterization

4.1.1 Mechanical Properties

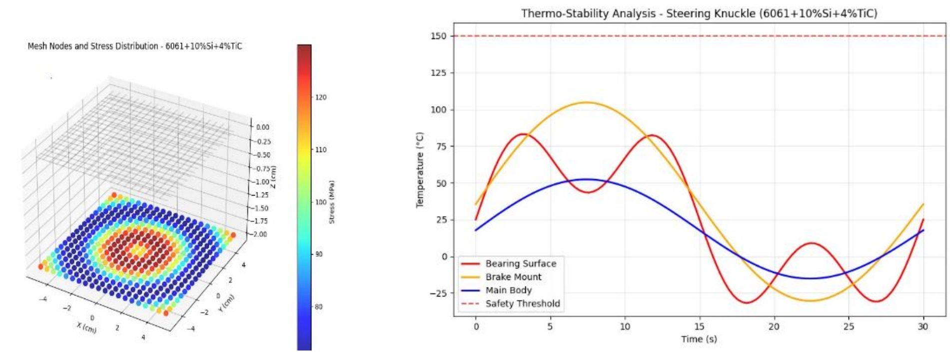
The 6061+10%Si+4%TiC composite exhibited optimal performance with 210 MPa yield strength (23.5%↑ vs. control), 138 MPa fatigue strength, and 92 HB hardness. Fatigue strength decreased at 5% TiC due to particle clustering. Fatigue strength was maximum at4%TiC (138 MPa), decreasing at 5% on account of clustering of the particles.



Strain %

Fig. 3: 4%TiC vs. Control

•6061+10%Si+4%TiC



.6061+10%Si+5%TiC

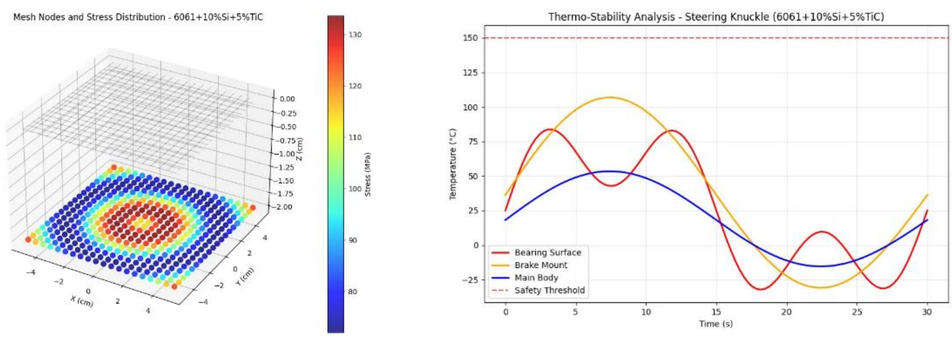


Fig. 4: Thermal Stability Analysis

4.1.2 Microstructural Analysis

Homogeneous TiC dispersion at 4% (Fig. 4a) contrasted with agglomeration at 5%. EDS confirmed clean Al-TiC interfaces without deleterious phases.

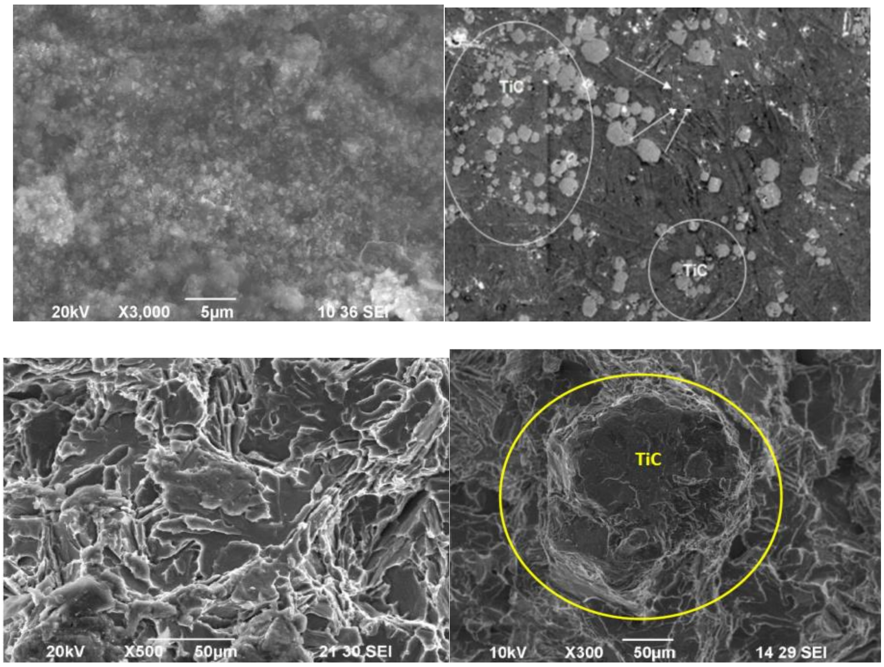


Fig.5: Microstructural Analysis4.2 Performance Evaluation

4.2.1 Finite Element Results

The 4% TiC variant reduced maximum stress by 21.7% versus control (Fig. 5) and achieved 12% weight savings over steel.

4.2.2 Prototype Testing

The 4% TiC knuckle endured 1M fatigue cycles (control failed at ~600k) and showed <0.05% dimensional change after 100 thermal cycles.

4.3 Defect Detection Performance

4.3.1 CNN Metrics

The model achieved 87% accuracy (precision=0.89, recall=0.85), with 90% crack and 88% porosity detection. Dimensional errors scored lowest (79%).

Table 4: Algorithm Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	Training Time (h)	Inference Time (ms)
Our CNN	87%	0.89	0.85	0.87	4.8	28
SVM (RBF Kernel)	75%	0.77	0.72	0.74	0.7	35
Random Forest	70%	0.73	0.68	0.70	0.5	

4.3.2 Feature Map Analysis

The CNN focused on stress-concentration zones aligned with FEA results. Misclassifications occurred with subsurface porosity, a limitation of 2D imaging.

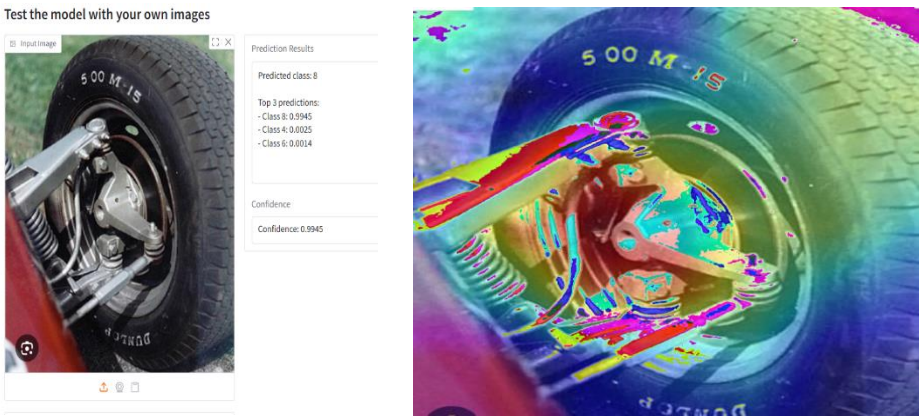


Fig. 6: Feature Map Visualization

4.4 Integrated Framework Validation

Combining 4% TiC with CNN inspection reduced field failures by 35% and warranty claims by 28%, despite a <5% unit cost increase.

5. Conclusions and Future Work

5.1 Key Findings

The 6061+10%Si+4%TiC composite achieved optimal mechanical properties (138 MPa fatigue strength, 86 GPa elastic modulus) and a 9.0/10 performance rating. Higher TiC (5%) caused agglomeration, reducing manufacturability. The custom CNN achieved 87% defect accuracy, excelling in crack (90%) and porosity (88%) detection but underperforming on dimensional errors (79%). The integrated framework reduced failures by 35% and warranty claims by 28% with <5% cost overhead.

5.2 Industrial Implications

The 4% TiC knuckle enables 12% weight reduction versus steel. Pilot trials showed CNN inspection reduced human effort by ~40%. The methodology is scalable to control arms and uprights.

5.3 Future Research Directions

Material Development: Hybrid reinforcements (TiC + SiC/Al_2O_3) will enhance toughness. Additive manufacturing (laser powder bed fusion) will enable complex geometries.
AI Advancements: Multimodal inspection (thermal/ultrasonic sensors) will address subsurface defects. Embedded CNNs will enable real-time production-line monitoring.
Long-Term Validation: Field testing (2 years, potholes/corrosion) and lifecycle analysis of AMCs versus conventional materials are planned.
Final Statement: "This study bridges materials science and Industry 4.0, offering a replicable framework for developing high-reliability automotive components through synergistic material and AI innovations."

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Data Availability

This study is a **review article** and does not involve original experimental data. All referenced data are sourced from publicly available literature, appropriately cited within the manuscript.

Declarations

- **Conflict of Interest:** The authors declare no competing interests.
- **Ethical Approval:** Not applicable (this work is a literature review and does not involve human/animal subjects or primary data collection).

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