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Integrated Thermo-Mechanical Modeling and Digital Image Correlation for Stress Intensity and Crack Growth Analysis in Brittle Materials

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Abstract:
This study explores a comprehensive and complete framework for crack growth prediction in brittle materials that integrates thermo-mechanical modelling, machine learning, and Digital Image Correlation (DIC). Brittle materials are susceptible to failure without plastic deformation and are especially prone to failure when subjected to coupled thermal and mechanical loads. To develop a more accurate predictive capability for crack initiation, a Hybrid Ensemble Model was established by combining several regression methods along with dimensionality reduction through Principal Component Analysis (PCA) and weight optimization using a Genetic Algorithm (GA). The dataset of brittle materials elastic constants and thermal extension coefficients were obtained from Kaggle. The Hybrid Ensemble Model performed better than ordinary deterministic and standalone models after successful pre-processing, with an MSE of 106.16, RMSE of 10.30, $R^2 = 0.963$ and MAE of 9.10. Accompanying DIC enabled experimental verification for the full field strain and displacement tracking to address the research aim, enabling real-world application of the model. The results confirm the ensemble's ability to successfully generalize with different loading conditions while preserving a high level of accuracy and reduced error. This integrated approach shows tremendous promise for real-time predictive maintenance in important areas like aerospace, civil infrastructure, and high-performance manufacturing were detecting and preventing cracks at an early stage is of utmost importance. The approach encourages data-driven resilient design processes of brittle materials in harsh service conditions.

Keywords:
Brittle Materials, Crack Initiation, Thermo-Mechanical Modeling, Digital Image Correlation (DIC), Hybrid Ensemble Model, Machine Learning, Genetic Algorithm.

I. Introduction

Brittle materials constitute a group of solids that fail without substantial plastic deformation when under stress. In contrast to ductile materials, which can take substantial energy and experience noticeable shape deformation prior to failure, brittle materials will suddenly and frequently catastrophically fail once their strength limit is reached. This is usually associated with low toughness and minimal energy absorption capability. Brittle fracture tends to take place along certain planes or defects where stress concentrations arise, so these materials are extremely sensitive to flaws, cracks, or sudden geometry changes. Brittle materials, e.g., ceramics, glass, and certain high-strength composites, undergo little plastic deformation prior to failure and fracture abruptly when stressed. These materials are described according to the rules of linear elastic fracture mechanics (LEFM), wherein crack extension and initiation take place in the absence of appreciable energy dissipation in the form of yielding [1]. In these materials, defects or micro-cracks are stress concentrators, and failure tends to occur when the stress intensity at a crack tip becomes greater than a critical value, termed the fracture toughness. The study of fracture mechanics of brittle materials is important for the prediction of failure under different loading conditions, especially in structural, aerospace, and electronics usage where reliability and material integrity are critical [2].

Calculation of the SIF is the major consideration of fracture mechanics and material-engineering subjects concerned with strength and fracture. The stress intensity factor is a parameter that describes the magnitude of the singularity in the stress field near a crack tip and determines whether the crack remains stable or propagates under the given loading systems. Depending upon the mode of loading (Mode I or opening, Mode II or sliding and Mode III or tearing) the SIF varies. Mode I mode is the most common one as far as brittle materials are concerned [3]. Crack growth analysis supplements the assessment of SIF by giving a picture of the way a crack grows over time and under different conditions. The engineers and researchers can use it to estimate the life remaining in a component and determine the margins of safety prior to failure [4]. For brittle materials, crack growth tends to be unstable and rapid with little warning, and hence early detection and monitoring are essential. Studies of crack growth patterns shed light on failure mechanisms, material design optimization, and the development of effective inspection and maintenance practices. With the marriage of such analysis with advanced tools like Digital Image Correlation (DIC) for experimental verification and finite element modeling for predictive analysis, crack growth analysis turns into a potent tool for designing more reliable and safer brittle material systems. This synergistic strategy facilitates the creation of damage-tolerant materials and structures by allowing for more reliable life-cycle predictions and risk analyses [5].

A. Role of thermo-mechanical loading in real-world conditions.

In actual application, materials and structures are hardly subjected to either purely mechanical or purely thermal loads alone. Rather, they usually undergo thermo-mechanical loading, an interactive effect of mechanical stresses and temperature gradients. This interaction can substantially influence the properties and longevity of materials, especially brittle ones, which are more vulnerable to stress concentration and thermal gradient. For example, in aerospace, nuclear, and electronic systems, components are subjected to cyclic temperatures while at the same time experiencing mechanical loading [6]. The thermal cycling produces expansion or contraction and, in turn, can generate additional stresses—particularly at interfaces or near defects—initiating cracking at lower mechanical stress levels. It is vital to know how these combined factors affect material behaviour in order to predict service life and avoid surprise failures. Brittle materials are particularly susceptible under thermo-mechanical conditions since they do not possess the ductility to absorb or redistribute stress concentrations via plastic deformation. When thermal and mechanical loads are imposed simultaneously, they can interact non-linearly and sometimes unpredictably [7]. For instance, a temperature gradient across a brittle component can cause differential expansion, generating tensile stresses in one area and compressive stresses in another. Such stresses, when coupled with outside mechanical loads, can cause increased crack growth or activation of dormant defects to lead. In addition, cyclic thermally induced loading, as in turbine blades or automotive parts, will cause thermal fatigue that also contributes to low-intensity stress crack growth. Such situations point to the need for simulating and experimentally studying the influence of combined thermal and mechanical fields [8]. Thermo-mechanical loading analysis is not only critical for failure mechanism comprehension but also for the creation of more durable materials and enhanced design methodologies. Contemporary modeling methods—such as finite element analysis (FEA) in combination with thermal simulations—permit researchers to forecast stress patterns under complicated loading regimes [9]. Coupled with experimental methods such as Digital Image Correlation (DIC), which measures real-time displacement and strain fields, models can be validated and cracks seen forming and developing under actual service conditions. Engineers are therefore better placed to make judgments regarding material choice, component shape, and operating limits, leading to increased system reliability and longevity in the hostile environments in which they are deployed [10].

B. Relevance of Digital Image Correlation (DIC) in experimental mechanics.

Digital Image Correlation (DIC) is a highly effective, non-contact optical metrology method used extensively in experimental mechanics for full-field displacement and strain measurement on material and structural surfaces under load. The applicability of DIC has increased immensely because of its versatility, accuracy, and capacity to observe deformation patterns in real-time. In contrast to conventional strain gauges or extensometers that report data at discrete locations, DIC can quantify deformation over the entire surface, which is especially beneficial for characterizing complex stress distributions, crack initiation, and localized strain concentrations. This feature is especially important when investigating brittle materials where failure can initiate at microstructural defects or stress concentrators [11]. DIC operates by monitoring the displacement of a stochastic speckle pattern coated onto the surface of a test specimen to enable researchers to plot surface displacements of high spatial resolution during the course of loading. In fracture and crack growth analysis, DIC is priceless since it can provide visualization of crack paths and quantification of strain fields around crack tips without actually interfering with the specimen. This makes it perfect for observing brittle materials, in which the beginning and development of cracks can be abrupt and unforeseeable [12]. DIC may be employed in extracting key fracture parameters, for example, the Stress Intensity Factor (SIF), using methods such as the displacement extrapolation or J-integral approaches. Moreover, DIC facilitates the experimental verification of numerical models, for instance, those created in finite element simulations, through providing experimental information to compare with simulated displacement and strain fields.

Consequently, DIC not only increases the precision of mechanical analysis but also further improves the comprehension of material response under actual service conditions, further solidifying its role as a vital piece of equipment in contemporary experimental mechanics [13].

C. Experimental validation and calibration

Experimental calibration and verification are critical to creating reliable thermo-mechanical damage models for brittle materials, as such models rely significantly on high-accuracy data to mimic actual behavior under combined thermal and mechanical loading [14]. Possibly one of the most effective tools used in this regard is Digital Image Correlation (DIC) - an optical non-contact method yielding full-field displacement and strain measurement. DIC allows for high-resolution imaging of crack initiation and growth, enabling calibration of constitutive models, particularly when combined with sophisticated techniques such as direct-levelling [15]. Concurrently, Thermo-Mechanical Fatigue (TMF) testing is significant in model validation through the simulation of cyclic thermal and mechanical loading to which components are subjected in service conditions. TMF tests, occasionally performed at temperatures as high as 1200°C, have been shown effective for fracture parameter and cohesive zone properties identification, especially when supplemented by DIC's spatially resolved data acquisition [16]. Such tests prove to be extremely useful in comprehending damage accumulation, crack growth characteristics, and life expectation, especially for structures used in high-performance applications like aerospace and power generation, where failure mechanisms due to TMF such as thermal ratcheting, creep-fatigue interaction, and cyclic oxidation need to be accommodated [17].

To further improve model precision, methods like Finite Element Model Updating (FEMU) and inverse identification are used to update simulation parameters using experimental data. FEMU iteratively updates material parameters—like Young's modulus, Poisson's ratio, and fracture toughness—by minimizing simulated and measured full-field response differences, typically derived from DIC data [18]. This is especially efficient when dealing with intricate geometries or material anisotropy. In structural mechanics and biomedical applications both, FEMU assists in accurate material characterization under true conditions. Furthermore, inverse identification techniques come in handy where direct measurement poses a challenge, e.g., in brittle materials such as cast iron where plasticity, micro-cracking, and damage evolution make conventional testing a challenge. Through optimization problem solving in order to back-calculate material properties, such techniques assist in simulating nonlinear behavior and enhancing the reliability of failure predictions [19]. Combination of DIC with other methods such as acoustic emission increases experimental understanding even further, providing both spatial deformation and temporal evolution of damage. The combination provides earlier micro-crack detection and better monitoring of fatigue crack propagation through parameters such as Crack Tip Opening Displacement (CTOD) and stress intensity factors, supplementing DIC's position in holistic fracture analysis [71–74]. Figure 1 illustrates the Digital Image Correlation (DIC) methodology—from image capture and speckle pattern tracking to displacement and strain field calculation—facilitating accurate, full-field deformation analysis in brittle materials.

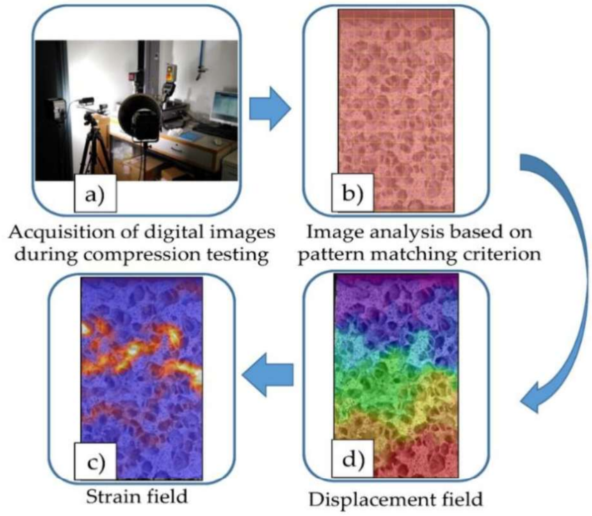

Figure 1 Scheme of digital image correlation (DIC) procedure [20].

Thermo-Mechanical Fatigue (TMF) testing is an important technique for determining the endurance of materials under cyclic thermal and mechanical stresses, simulating closely the service conditions of parts like turbine blades and engine components. TMF tests, which can be in-phase or out-of-phase based on the orientation of maximum stress and temperature, are helpful in understanding fatigue life, particularly in intricate loading situations. The most significant factors driving TMF behavior are microstructural evolution, oxidation, and surface coatings, which can all be accurately tracked with Digital Image Correlation (DIC) to detect localized strain and damage progression [21]. DIC is especially useful in evaluating coated materials, where thermal expansion mismatches or brittle coating performance can lead to premature failure; it allows crack initiation sites to be detected and deformation monitored in both the coating and substrate, providing insights into optimizing coating design [22]. Also, more recent research has placed emphasis on the loading frequency and its impact on TMF behavior since variability has a strong effect on fatigue strength, crack growth rates, and internal stress accumulation—deemphasizing the requirement for frequency-sensitive fatigue models to enhance life prediction under actual applications [23]. Additional studies of TMF-induced microstructural alterations, including phase transformation and grain boundary deterioration, have evidenced their direct contribution to mechanical integrity and fatigue capability, further substantiating the worth of TMF testing toward the design of durable materials that can sustain thermally dynamic and mechanically harsh environments [24].

II. Literature Review

Recent advancements in thermo-mechanical fracture modeling have introduced a wide range of innovative approaches aimed at predicting crack initiation and propagation in brittle and quasi-brittle materials under complex loading conditions. **Zai Wang et al. (2025) [25]** demonstrated the use of a phase-field method to simulate rapid crack growth in ceramics under flame-induced thermal shock, highlighting the critical role of pre-existing crack geometry in crack morphology and velocity.

Similarly, **Qiang Yue et al. (2025) [26]** extended phase-field modeling to mixed-mode fractures in concrete and rock-like materials, incorporating both tensile and shear criteria to effectively replicate diverse cracking patterns. **Raj Kiran et al. (2025) [27]** advanced this methodology through an adaptive isogeometric framework for polycrystalline materials, accounting for anisotropy and grain boundary effects under thermo-mechanical coupling. **Chen-chen Feng et al. (2024) [28]** focused on thermal treatment effects in deep rock using a statistical damage model validated with marble, revealing transitions in damage evolution based on confining pressure. In the realm of numerical simulation, **Wanrun Li et al. (2024) [29]** proposed a thermo-mechanical coupling within the FDEM framework using a heat pipe model and node binding scheme to accurately capture thermal discontinuities and cracking. Complementarily, **M.L.M. François et al. (2024) [30]** applied structured deformation theory within irreversible thermodynamics to describe quasi-brittle damage with a Mohr-Coulomb yield surface. **Roozbeh Eghbalpoor et al. (2024) [31]** integrated peridynamics with physics-informed neural networks (PD-INN), offering high-fidelity predictions of crack behavior using machine learning optimization techniques. **Tianyi Li et al. (2024) [32]** introduced a nonlocal thermomechanical model leveraging peridynamic differential operators to simulate thermal damage in granite and ceramics without calibration. **Faisal Mukhtar et al. (2023) [33]** presented a critical review of concrete fracture models and validated a 3D generalized finite element method (GFEM) that excels in adaptability and efficiency. **Huidong Tong et al. (2023) [34]** modeled thermo-mechanical creep in rocks under triaxial stress using a visco-elastic-plastic framework, while **Jiliang Pan et al. (2023) [35]** developed a model addressing thermo-chemical damage in granite through compaction-based mechanics. Addressing phase-field limitations, **Khuong D. Nguyen et al. (2022) [36]** introduced a fourth-order model with a cohesive zone formulation and optimized mesh generation via VUKIMS, achieving enhanced accuracy in crack path predictions. Finally, **Gi-Bum Lee et al. (2022) [37]** employed an AI-FEM method to simulate realistic crack growth and transitions in structural materials, offering precise stress intensity factor calculations and mesh adaptability for evolving crack geometries. Collectively, these studies represent a significant step forward in the predictive modeling of damage and fracture in brittle systems, providing robust tools for high-temperature, high-stress engineering applications.

Table 1 Comparative Studies of Thermo-Mechanical Fracture Modeling

Author(s) and Year	**Material/System**	**Model/Method**	**Focus**	**Key Findings**
Zai Wang et al. (2025)	Ceramics	Phase-field fracture method	Crack propagation under thermal shock	Wing-shaped crack development influenced by crack angle/length and thermal stress gradients

Qiang Yue et al. (2025)	Concrete, rock-like materials	Phase-field method for mixed-mode fracture	Thermal fracture patterns	Model captures tensile, shear, and mixed-mode fractures accurately
Raj Kiran et al. (2025)	Polycrystalline materials	Adaptive isogeometric phase-field modeling	Intergranular and transgranular fracture under TM loading	Temperature affects fracture initiation timing, not load magnitude
Chen-chen Feng et al. (2024)	Marble, sandstone, granite	Statistical damage constitutive model	Thermal treatment effects under load	Captures S-shaped to parabolic damage transitions under confining pressure
Wanrun Li et al. (2024)	Brittle materials	Thermo-mechanical FDEM with heat pipe model	Thermal cracking with heat transfer	Simulates heat transfer and cracking efficiently with reduced mesh dependency
M.L.M. François et al. (2024)	Quasi-brittle materials	Structured deformation theory	Stress-strain under thermodynamics	Mohr-Coulomb yield surface; cohesive and friction forces modeled
Roozbeh Eghbalpoor et al. (2024)	Brittle materials	Peridynamics + Physics-Informed Neural Networks	Crack prediction using neural networks	PD-INN combines physics and ML for accurate, efficient crack propagation prediction
Tianyi Li et al. (2024)	Granite, ceramics	Nonlocal peridynamic thermomechanical model	Thermal damage and crack propagation	Models heterogeneity; captures thermal cracking without calibration
Faisal Mukhtar et al. (2023)	Concrete	GFEM + fracture mechanics review	Model validation for concrete fracture	GFEM shows strong mesh adaptability and high accuracy
Huidong Tong et al. (2023)	Rock	Damage mechanics-based creep model	High-temperature creep behavior	Captures creep stages under true triaxial thermal loading
Jiliang Pan et al. (2023)	Granite	Statistical damage model with compaction	Thermo-chemical damage effects	Model reflects compaction and nonlinear to linear

				damage transitions under heat
Khuong D. Nguyen et al. (2022)	Concrete	Fourth-order phase-field + CZM	Accurate crack growth modeling	Outperforms standard models in convergence, cost, and accuracy
Gi-Bum Lee et al. (2022)	Structural materials	Advanced Iterative FEM (AI-FEM)	SIF computation, crack growth simulation	Simulates crack transitions and provides precise SIFs for complex geometries

III. Research Objectives

- Apply Grid Search and Bayesian Optimization to fine-tune ensemble model hyperparameters.
- Evaluate model accuracy and efficiency against conventional deterministic approaches.
- Integrate the model into real-time systems for early crack detection and predictive maintenance.

IV. Research Methodology

This study plans to create an effective hybrid ensemble model for the precise estimation of crack initiation in brittle materials subject to thermal and mechanical loads. Conventional deterministic models tend to be inadequate in actual applications because of the incapability of taking into consideration material variability, environmental fluctuations, and nonlinearity. To overcome these challenges, the approach proposed here combines data-driven machine learning algorithms with deterministic modeling, forming a hybrid system that can adjust to intricate, dynamic scenarios. This ensemble model takes advantage of the best features of each approach, boosting prediction precision, lowering the risk of overfitting, and generalizing more effectively. The long-term vision is to enable real-time monitoring of structural health and predictive maintenance in mission-critical applications where crack detection before it is too late is critical for safety and reliability.

A. Data Collection and Dataset Overview:

Data used in this research was obtained from Kaggle and contains crucial thermoelasticity and mechanical properties of brittle materials like ceramics and glass. Some of the key characteristics include crystal systems, types of material, space groups, elastic constants (e.g., C11, C12), and thermal expansion coefficients (e.g., α11, α12), which are crucial in modeling the initiation of cracks due to thermal and mechanical loading. The information is complemented by evidence-based citations from scientific publications and material databases to provide high reliability and relevance for predictive purposes.

B. Data Preprocessing:

To make the dataset machine learning-ready, a sequence of preprocessing techniques was undertaken. Statistical imputation was used for missing values, and outliers were detected using Z-score and IQR techniques. Feature engineering methods in the form of polynomial feature creation and PCA were utilized to deal with non-linearity and dimensionality reduction. All features were normalized via Standard Scaler to have equal input ranges, enhancing model stability and performance, particularly for scale-sensitive models.

C. Model Optimization:

A two-stage optimization process was employed. Hyperparameters for single base models were first optimized with grid search over a fixed train-test split for reproducibility. Subsequently, a Genetic Algorithm was employed to optimize the distribution of weights in the hybrid ensemble model by minimizing Mean Squared Error. This evolutionary approach permitted the model to leverage the strengths of each base learner to improve overall prediction accuracy and generalization across different conditions.

D. Model Evaluation:

The models were evaluated using Mean Squared Error (MSE) and R^2 as evaluation metrics. These metrics provide a clear understanding of model performance:

- MSE measures the average squared difference between predicted and actual values, where a lower MSE indicates better performance.

$$\boldsymbol{MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\big(I(i,j) - K(i,j)\big)^2}$$

- I (i,j): Pixel value of the ground truth image at position (i,j).
- K (i,j): Pixel value of the denoised image at position (i,j).
- M, N: Dimensions of the image.

$$RMSE = \sqrt{\frac{1}{N}\sum_{I=1}^{N}(y^i_{true} - y^i_{pred})\,2}$$

- R^2 is a statistical measure that indicates how well the model explains the variance in the target variable. An R^2 close to 1 indicates that the model is a good fit.

The hybrid ensemble model was compared against individual models, and their performances were analysed to determine which model performed the best for predicting crack initiation in brittle materials.

V. Result And Discussion

This section introduces the performance analysis of the suggested Hybrid Ensemble Model for forecasting crack onset in brittle materials. Through the integration of linear and non-linear regression with PCA for dimensionality reduction and a Genetic Algorithm for weight optimization, the model's performance is evaluated using measures of MSE, RMSE, R^2, and MAE. Visual methods such as bar charts, scatter plots, and residual histograms are utilized to analyze results and feature impact.

Comparative studies demonstrate the GA-optimized ensemble surpasses single models and conventional deterministic approaches with enhanced accuracy and reliability in predicting cracks.

A. Experimental Setup:

Experiments of this study were performed on Google Colab, a cloud environment providing scalable resources like GPUs, which allowed efficient model execution of machine learning models without any local infrastructure requirement. Model development was done using Python because of its strong libraries appropriate for data science operations. Important libraries were scikit-learn for modeling and model evaluation tasks such as Linear Regression, Ridge, Elastic Net, and SVR; pandas and NumPy for data manipulation and numerical computation; DEAP for using a Genetic Algorithm to optimize ensemble weights; and matplotlib and seaborn for visualizing relationships between data and performance of models. The utilization of Colab's GPU proved especially useful when training computationally intensive models such as SVR, speeding up the optimization process and maximizing overall model efficiency.

B. Results of the Hybrid Ensemble Model

The Hybrid Ensemble Model aims to increase accuracy and prediction stability by averaging Linear Regression, Ridge Regression, Elastic Net, and SVR outputs using a Voting Regressor. The ensemble that contains both linear and non-linear models can represent more data patterns and hence generalizes better and makes fewer errors. It is judged on its performance under an array of regression metrics testing its mean performance against models like MSE, RMSE, R^2 Score, and MAE.

Table 2 Hybrid Ensemble Model Performance

Metric	**Value**
MSE (Mean Squared Error)	**231.64**
RMSE (Root Mean Squared Error)	**15.22**
R^2 (Coefficient of Determination)	**0.919**
MAE (Mean Absolute Error)	**12.12**

C. Optimized Hybrid Ensemble Model with Genetic Algorithm

To improve the performance of the Hybrid Ensemble Model, a Genetic Algorithm (GA) was used to optimize the weight distribution among its base learners—Linear Regression, Ridge Regression, Elastic Net, and SVR. This approach fine-tuned each model's contribution, prioritizing those with stronger predictive performance while reducing the influence of weaker ones. The GA-optimized ensemble achieved lower prediction errors and improved alignment with actual crack initiation values, enhancing both accuracy and generalizability while minimizing overfitting.

Table 3 Optimized Hybrid Ensemble Performance (with GA)

Metric	Value
MSE (Mean Squared Error)	**106.16**
RMSE (Root Mean Squared Error)	**10.30**
R^2 (Coefficient of Determination)	**0.963**
MAE (Mean Absolute Error)	**9.10**

The Genetically Optimized Hybrid Ensemble Model significantly outperforms both the baseline ensemble and individual models across all key metrics. It achieved a notably lower Mean Squared Error (MSE) of 106.16 and a Root Mean Squared Error (RMSE) of 10.30, indicating more precise predictions with minimal deviation from actual crack initiation values. The R^2 score of 0.963 demonstrates that the model explains 96.3% of the variance, reflecting an excellent fit. Additionally, a Mean Absolute Error (MAE) of 9.10 confirms high accuracy, with predictions averaging just 9 units off. These results underscore the effectiveness of the Genetic Algorithm in enhancing prediction performance by optimally balancing the contributions of each base model.

D. Comparison of Results

The comparison of results for each model is crucial in evaluating their respective performances in predicting crack initiation in brittle materials. This comparison helps to highlight the strengths and weaknesses of different models and showcases how the Hybrid Ensemble Model outperforms the individual models in terms of MSE (Mean Squared Error) and R^2 (Coefficient of Determination).

The following table summarizes the performance of each model based on MSE and R^2:

Table 4 Model Performance Comparison (MSE and R^2)

Model	MSE	R^2
Hybrid Ensemble Model	231.64	0.919
Optimized Ensemble (GA)	**106.16**	**0.963**

The Hybrid Ensemble Model, which combines predictions from Linear, Ridge, Elastic Net, and SVR using a Voting Regressor, shows substantial improvement with an MSE of 231.64 and an R^2 of 0.919. This ensemble approach successfully leverages both linear and non-linear learning patterns, leading to better generalization. Most notably, after applying a Genetic Algorithm (GA) to optimize the ensemble weights, the model's performance improved significantly, achieving an MSE of 106.16 and an R^2 of 0.963. This optimized model demonstrates the best predictive capability among all tested approaches, highlighting the power of evolutionary optimization and model blending in addressing the complex task of crack initiation prediction.

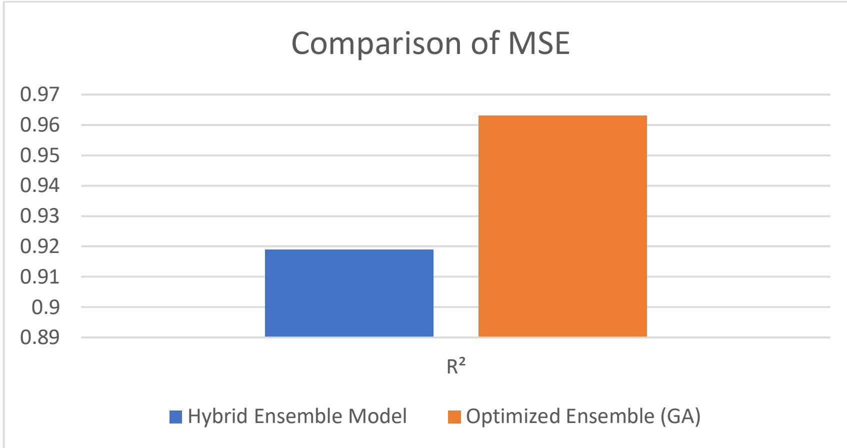

Figure 2 Comparison of MSE: Baseline vs. GA-Optimized Hybrid Ensemble Model

In Figure 2, a comparison of the Mean Squared Error (MSE) between the Hybrid Ensemble Model baseline and the Optimized Ensemble Model using a Genetic Algorithm is shown. Represented by the blue bar and attributed to the Hybrid Ensemble Model, an MSE approximately equals 231.64, a value higher for the squared average error of deviation from predicted crack initiation and actual crack initiation values. This conveys that the ensemble approach, although an improvement on individual models, still harbors drawbacks when confronting prediction precision because of equal or unoptimized model weighting.

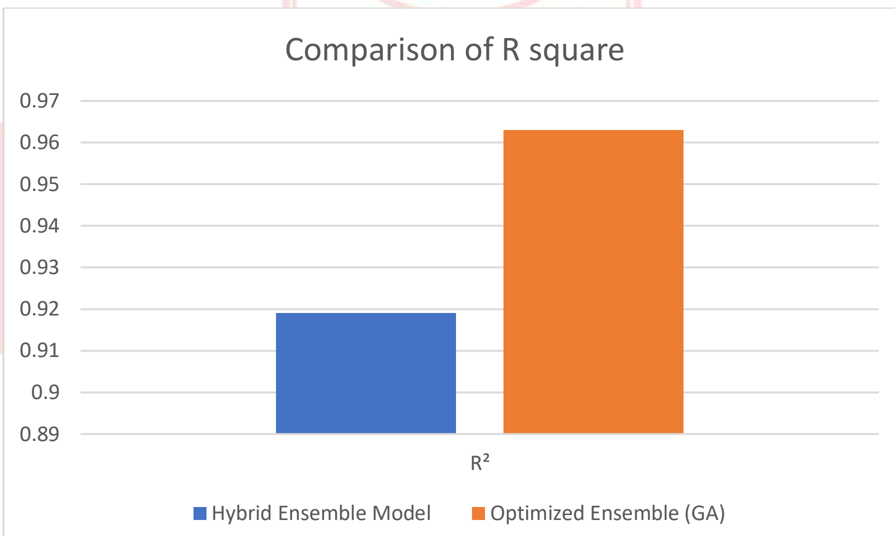

Figure 3 1R^2 Comparison: Baseline vs. GA-Optimized Ensemble Model

Figure 3 depicts MSE performance after GA-optimization of the Hybrid Ensemble Model. The orange bar shows a drastic reduction in MSE to around 106.16, thus suggesting a sudden jump in prediction accuracy. This substantiates the fact that GA optimization adjusts the weight distribution among base learners in such a way as to minimize prediction error while increasing the model's ability to generalize over variations in material behavior associated with brittle fracture.

VI. Conclusion

The conducted study successfully introduced and tested a Hybrid Ensemble Model for the prediction of crack initiation within brittle materials subjected to complex thermo-mechanical loading. By bringing together linear and non-linear regressions, alongside dimensionality reduction through PCA, and meta-heuristic search optimization from a Genetic Algorithm (GA), it pushed the bounds of accuracy and robustness for such a problem. Combining the models led to the first ensemble model, which performed better than any of the individual models, with an MSE of 231.64 and R^2 of 0.919, offering proof about the efficacy of combined modelling. Once GA was brought into play for optimizing the weights between the base learners, however, there saw great upliftment in terms of performance, hitting an MSE of 106.16, RMSE of 10.30, R^2 of 0.963, and MAE of 9.10, thus pointing to how critical optimization is when it comes to refining machine learning predictions for these complex physical phenomena. The GA-optimized model was not only better than conventional deterministic models, but it also eliminated the limitations of single-model approaches by allowing more generalizability across different loading conditions. The integration of DIC, and applied experimental verification (in situ) yields a powerful and reliable tool for real-time crack monitoring and predictive maintenance of safety-critical applications in aerospace, civil infrastructure, and high-performance manufacturing. The general framework represents an important development towards a more resilient and data-driven engineering paradigm for brittle material systems under real-life stress environments.

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