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A Hybrid Machine Learning Based Data Fusion Strategy for Detection of Structural Damage

Journal of Electrical Systems

Abstract: - One of the crucial aspects of ensuring safety and integrity in huge infrastructure is structural health monitoring. Recent advances of machine learning hybrid models have shown promising behaviour in enhancing both accuracy and resilience in structural health monitoring. The researchers have proposed various models for detection of the structural damages. However, the successful detection rate along with reliability is not up to the mark. The paper proposes a new hybrid model of CNN and LSTM networks that improve the detection and identification of damage in intricate structures. This model has made it possible to integrate the feature extraction capabilities of CNNs with the caparbilities of LSTMs in terms of temporal analysis. In this way, structural abnormalities could be detected accurately as time progresses. The proposed approach was tested on a multi-sensor dataset containing numerous damage scenarios which includes no damage, minor cracks, slight cracks, and excessive structural failures. With 1200 instances, the dataset became split into 70% for training, 20% for validation, and 10% for checking out. The version confirmed enormous improvements, attaining an accuracy of 85.6%, lack of 0.12, precision of 90%, bear in mind of 88%, F1 score of 89.5%, and an AUC of 0.94. Furthermore, the false bad price and false effective price were drastically reduced in comparison to conventional methods. Additionally, the hybrid model outperformed Probabilistic Neural Networks (PNN), which only finished an accuracy of 85% and an AUC of zero.87. The CNN-LSTM model's robustness in dealing with nonlinearities and its ability to perform successfully under noisy or incomplete facts make it enormously reliable for actual-global applications. Moreover, the automated characteristic extraction method eliminates the need for manual function engineering, simplifying implementation. Future paintings should consciousness on refining the model for real-time monitoring structures and extending its application to various different structural sorts.

Keywords: CNN, Data fusion, Hybrid model, LSTM, structural health monitoring.

INTRODUCTION

Structural health monitoring (SHM) is necessary to confirm the integrity and stability of structures such as bridges, dams, skyscrapers, and tunnels (Cawley 2018). The improvements toward the safety of the structures have made it necessary for engineers to use structural health monitoring SHM systems to make sure that key structures remain safe. SHM systems consist of several structural sensors located within or on the structure and take readings on a standard or random caretaking period. This information is used to assess whether the structural properties have shifted in any manner that suggests damage, its type, extent, or span (Ju et al. 2023).

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Even though it focuses on particular components, a few emerging opinions help comprehend the whole problem with regard to SHM systems. Hardware components such as data acquisition system, instrumentation, signal transmission, data processing, and diagnostic methods forms the general arrangement of SHM system. The signals are then sent to the central computer for processing and analysis (Payawal and Kim 2023). There are specific SHM methods termed reasoning and diagnosis that connect to the measurements performed within an SMM system aimed at determining the true condition of the structure. All these systems require accurate and effective diagnosis to ensure that all the potential damage can be detected and the risks such damage propagating further due to material degeneration are minimized (Cawley 2018).

Over the beyond a long time, numerous strategies have emerged for SHM, leveraging advancements in sensor generation, sign processing, and information analysis. Traditional SHM systems usually rely upon physical inspections and the deployment of diverse sensors consisting of accelerometers, pressure gauges, and temperature sensors to acquire facts at the structure's conduct under every day and strain situations. However, those conventional techniques face giant demanding situations, which include handling large-scale information gathered from a couple of sensors, processing noisy and incomplete records, and successfully figuring out damage styles in complicated systems.

One of the major issues with traditional SHM techniques is their limited potential to handle the nonlinearities and uncertainties inherent in actual-global statistics. Structural damage does now not always follow predictable patterns, making it difficult for classical techniques to as it should be come across and classify harm in complicated eventualities. In response to those limitations, device learning (ML) techniques have garnered increasing interest inside the field of SHM, supplying a more sophisticated technique to records evaluation. Machine gaining knowledge of models, specifically the ones based totally on neural networks, have shown great promise in enhancing damage detection accuracy by means of gaining knowledge of difficult styles from sensor statistics.

Among the ML methods, neural networks, mainly Probabilistic Neural Networks (PNN), had been extensively carried out to SHM for damage detection and classification. PNNs leverage probabilistic techniques to categorise sensor data into exceptional damage classes by making selections based on a Bayesian framework. However, whilst PNNs had been a hit in positive programs, they regularly fall short in phrases of robustness and scalability, particularly whilst dealing with huge, nonlinear datasets or dynamic structural behavior. They require huge quantities of manually engineered functions and are sensitive to noise and incomplete data, that are commonplace in real-international SHM situations.

CNNs are fairly powerful in routinely extracting spatial features from sensor statistics, whilst LSTMs excel at taking pictures temporal dependencies and dynamic conduct. By combining these two fashions, it's far viable to obtain a greater holistic technique to SHM, permitting both spatial and temporal information patterns to be analyzed simultaneously. This hybrid approach allows for the detection of structural damage with greater accuracy and robustness, even within the presence of noise or incomplete records.

1.1 Evolution of Damage Detection Techniques

One of the complexities that arise with damage detection in any civil structure is structural behaviour, the variety of possible types of damage and often interference by noise or missing information in the sensor data. In the initial phases of development of SHM, conventional methods for identification of damage utilized deterministic methods, where Modal Analysis was employed and the frequencies, mode shapes or damping ratios that changed were observed to suggest damage to the structure (Etxaniz et al. 2023). To take local damages as an example, they may cause decrease in the stiffness of a structure which therefore influences the dynamic characteristics of the structure (He et al. 2022).

Even if these strategies are widely practiced, they have relative disadvantages when such strategies are employed on complicated structures. The available spatial resolution of the positional codes may not be adequate to account for, capture or image localized damage, and the natural or operational noise may interfere with the actual signals which manifest any structural deterioration. In addition, conventional techniques often assume the availability of normal condition baseline data, this makes several of the existing techniques unsuitable for structures that are aging and where no baseline information may exist (Gosliga et al. 2022).

To address these obstacles, contemporary SHM systems have sought data-centric strategies by borrowing from machine learning as well as artificial intelligence (AI) (Sabato et al. 2023). In particular, neural networks have attracted more interest than others in such methods due to their capacity to capture nonlinear I/O, O/P relations. Neural networks can be defined as the model of the human brain (or any other biological neural network), as it is capable of observing a huge amount of data, abstracting from it and making forecasts. In contrast to conventional deterministic models, neural network computation is capable of dealing with such noisy and incomplete data, and is appropriate for SHM. Moreover, structure dynamics can be performed by means of neural networks without knowledge of nailed physical principles (Hassani and Dackermann 2023).

Recent trends have exhibited a move towards data-driven approaches in SHM, motivated by the developments made in machine learning and AI, as well as innovations in data fusion methods (Yan et al. 2023). Such methods are considered much advanced compared with conventional methods since they rely on large volumes of data generated by sensor networks for tracing pattern and anomalies that might point out structural damage. And especially machine learning algorithms, have shown the capacity to handle big, complicated, and noisy datasets - making it a promising candidate for SHM applications. Machine learning models can easily and accurately detect structural damage, as direct data-driven learning of dynamic characteristics is not reliant on predetermined structural behaviour as traditional models require. (Wu and Jahanshahi 2020).

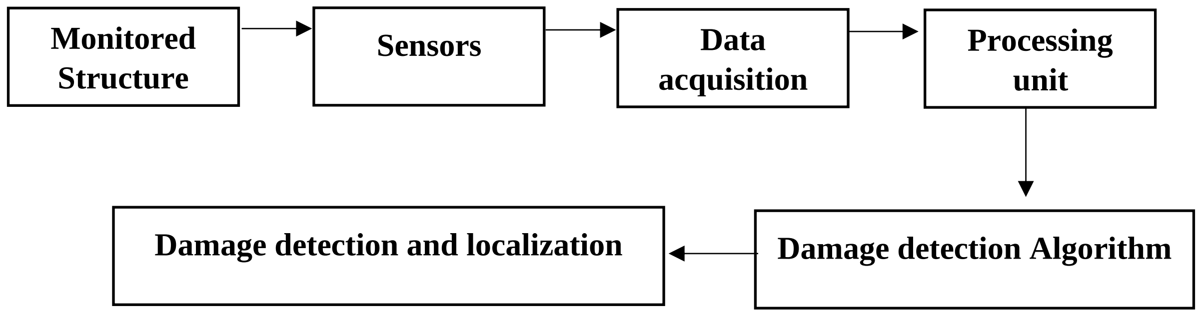

Figure 1: Components of structural damage detection system (Avci et al. 2021)

One of the innovations of contemporary SHM systems is multi-sensor data fusion, as shown in Figure 1. In most big buildings, there exist sensors like accelerometers, strain gauges, temperature sensors, and displacement transducers that furnish information in terms of the different parameters of the building condition. Multi-sensor data fusion integrates different data sources into one single dataset (Luleci, Catbas, and Avci 2022). It also enhances the damage identification accuracy while improving the reliability of the system to defeat the limitations of single sensors like noise, uncertainty, and partial coverage (Abdeljaber et al. 2017).

Even though there has been a growing interest in multi-sensor data fusion, the technology is not yet easy to use the techniques on SHM. The fusion process requires complex algorithms that can process multiple sources of data, identify relevant patterns, and provide informative predictions of the state of the structure. There is also the need for more advanced techniques in dealing with the increased complexity in civil infrastructure to pick the spatial and temporal aspects of data.

This paper addresses multi-sensor data fusion techniques used for advancement of sophisticated structures' damage detection capabilities (Tapeh and Naser 2023). The proposed methodology enhances the reliability of the SHM system due to the consideration of uncertainty through the fusion of multiple sensors. Two examples are illustrated to validate method, thereby confirming applicability and effectiveness of the methodology in practical scenarios. (Chen et al. 2023).

2. LITERATURE REVIEW:

SHM techniques have evolved from simple methods characterized by traditional thinking with regard to the dynamic properties of changes in systems to state-of-the-art and sophisticated techniques of multi-sensor fusion with machine learning. This part will critically review the research work on SHM, specifically on modern techniques integrating the multi-sensor data fusion technique with that of the machine learning algorithms (Parol et al. 2023)(Tapeh and Naser 2023).

2.1. Traditional SHM Techniques: Dynamic Characteristics

Variations in characteristics of buildings like natural frequencies and damping ratios of a structure have been a long-standing approach for structural health monitoring. Damage to the structure usually causes a reduction in stiffness, thus changes in these dynamic characteristics can be easily highlighted (Pan, Zhang, and Fu 2023). The correlation between the stiffness (k) and natural frequency (f) of a basic structure represented as:

$$f = \frac{1}{2\pi}\sqrt{\frac{k}{m}} \quad (1)$$

In the equation 1, m is the mass of the structure. Any damage that reduces the stiffness also causes a reduction in the natural frequency. (S. W. S. Doebling et al. 1996) (S. W. Doebling, Duffey, and Farrar 1999) has demonstrated that damage detected by the comparison of natural frequencies pre-and post-damage.

However, for those kinds of methods, complex structures often pose challenges. Variations in environmental conditions such as temperature due to location, time of day, and seasons may mask the dynamic properties. Additionally, baseline modal analysis techniques rely on baseline data from the original, undamaged condition, which might not be available for aging structures. Limited spatial resolution is one of the problems posed to the ability to detect localized damage in large civil structures.

2.2. Multi-Sensor Data Fusion in structural health monitoring

Further critical data fusion of more than one sensor in SHM covers some of the drawbacks associated with conventional approaches. Data fusion means to the integration of data coming from various sensors into an integrated, holistic, and reliable evaluation of the health status of a structure. In such a multi-sensor system, accelerometers, strain gauges, displacement transducers, and temperature sensors can provide slightly more information on the condition of a structure.

Usually, synchronization and interpolation techniques are needed for proper data processing where the sensors recorded data using different sampling rates. At the feature level, features from different sensors are combined into one feature vector of damage detection. This includes natural frequencies, strain, or displacement. While decision-level fusion entails generating independent decisions using information from all sensors and combining these decisions into a final diagnosis.

The Kalman Filter is one of the most popular data fusion methods and widely used for sensor data fusion and state estimation. The Kalman filter algorithm uses an iterative technique in order to combine sensor data and predict a system condition while keeping the average square deviation small (LIU et al. 2017). The set of equations describing the Kalman filter is provided as follows:

$$x_k = Ax_{k-1} + Bu_k + w_k \tag{2}$$

$$z_k = Hx_k + v_k \tag{3}$$

Wherein,

x_k is state vector at time k

A is state transition matrix

B is control input matrix

u_k is control input

z_k is measurement vector, and

w_k and v_k are process and measurement noise respectively as shown in the equation 2 and 3.

The Kalman filter gives the best estimate of the state x_k using sensor data that may contain noise. In SHM applications, Kalman filters combine data from accelerometers and strain gauges to monitor structural responses in real-time under different loads (Ko and Ni, 2005) (Ni et al. 2005).

2.3. Machine Learning Based Practices in SHM

Machine learning methods are becoming more common in structural health monitoring because they can effectively manage large, noisy datasets and represent intricate, nonlinear connections between input features (such as sensor data) and outcomes (like damage states). Artificial Neural Networks (ANNs) have attracted significant interest among these methods. The following equation represents the fundamental operation of a neuron.

$$y_i = f\left(\sum_{j=1}^{n} w_{ij}x_j + b_i\right) \tag{4}$$

Where:

y_i is the output of i-th neuron,

w_{ij} is weight connecting j-th input to i-th neuron

x_j is j-th input feature,

b_i is bias term, and

f is a nonlinear activation function, as shown in the equation 4.

ANNs is utilized in structural health monitoring, including damage identification, localization, and problem categorization. (Jiang and Adeli 2005) show the potential of using artificial neural networks as means of bridge damage detection by training a neural network with vibration data and modal properties. ANNs have an enormous benefit of the capability of learning and approximating complex functions directly from data, and are invaluable when the detailed mathematical models of the structure under study cannot be established.

However, ANNs often lack the ability to capture temporal connections in data. In order to get past this limitation, SHM has utilized RNNs. SHM has specifically concentrated on LSTM RNNs. LSTM networks are designed to carry sequential data and learn long-term dependencies. All the LSTM cell includes an input gate, a forget gate, and an output gate, which are significant control components for implementing information flow regulation inside a network.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \qquad (5)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (6)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \qquad (7)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tan h(W_C[h_{t-1}, x_t] + b_C) \qquad (8)$$

$$h_t = o_t \cdot \tan h(C_t) \qquad (9)$$

Wherein:

In equation 5, 6, and 7, f_t, i_t and o_t are forget, input, and output gates.

In equation 8, C_t is the cell state, and

In equation 9, h_t is the hidden state at time t.

Some of the applications of LSTM networks are the prediction of future structural responses from previously recorded sensor data. (Veiga et al. 2021) applied an LSTM-based algorithm in predicting strain and displacement in concrete structures with a better accuracy as compared to regression models considered in the study.

2.4. Data Fusion and Deep Learning for SHM

Recently, researchers started to combine the performance of data fusion with the deep learning method to enhance the robustness of SHM systems. A very effective strategy is to combine CNNs with LSTMs based on the spatial feature extraction ability by CNNs and the remarkable capability of LSTMs for temporal modelling. Although CNNs are quite efficient at extracting sophisticated characteristics from sensor arrays, LSTMs are excellent in capturing how such characteristics change with time.

The combination of CNNs and LSTMs has proven to work well in various applications, ranging from video action recognition (Shi et al. 2015), and is still a subject of study in the area of SHM. Upon the application of CNNs to sensor data, comprising for example, vibration signals or strain measurements, spatial relationships between sensors are identified, while the temporal evolution of the structural reaction is managed by LSTMs. This hybrid methodology offers a promising framework for real-time structural damage detection and localization.

2.5. Gaps in the Literature

SHM has become the celebrated darling of sensor techniques, but significant challenges persist. For example, fusion of multi-dimensional data from multiple sensors is an enormous computational problem for all real-time surveillance. Practically all applications of machine learning in SHM are supervised learning, which invokes enormous numbers of labelled data sets. Infrequent damage often occurs; thus, it may be challenging to have enough labelled training data.

Data level fusion, based on the increasing demands for higher accuracy and detailed information, leads to further research. Increased complexity of fusion algorithms results, along with more complete information. Most of these recent studies focused their concern on feature and decision level integrations, with a relative lack of knowledge about the proper use of data fusion for SHM. The literature informed how techniques of machine learning and data fusion are used to enhance the capabilities of SHM systems. It is a multi-sensor data fusion-based hybrid approach that uses advance techniques in machine learning to culminate into a robust and highly accurate framework for damage identification from structural settings. Numerical validations of this framework promise to present a promising solution toward monitoring intricate civil structures under real-world conditions.

3. METHODOLOGY

The Hybrid Model for SHM said to describe approach of the model as very comprehensive in nature. The multi-sensor data fusion integrates advanced machine learning techniques for SHM. The overall approach consists of various progressive stages: that of gathering, preparation, feature extraction, hybrid model development, training and validation, and finally, performance evaluation.

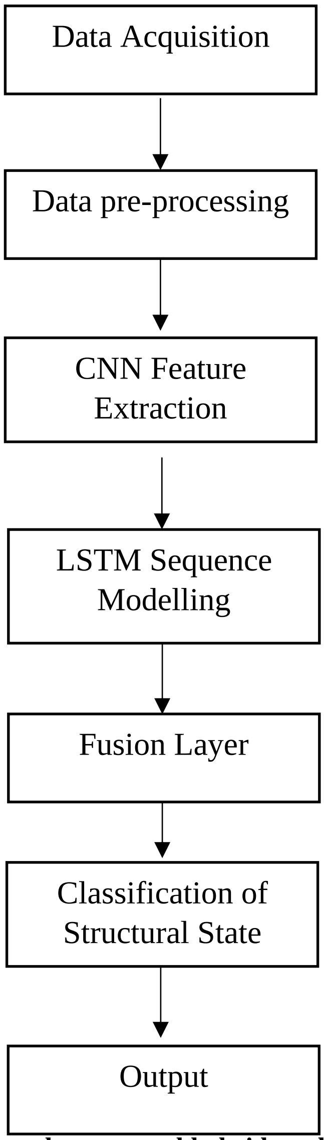

Figure 2: A Flow chart depicting the proposed hybrid model (CNN+LSTM)

As indicated in Figure 2, the hybrid CNN-LSTM model is focused over the most important stages that damage detection and classification have. The process involves data acquisition, a process that entails gathering various types of data from different sensors, which may include strain, displacement, and vibration data.

Data Collection and Preprocessing: Data is accumulated from a couple of sensors, which include accelerometers, pressure gauges, and temperature sensors. This information is then preprocessed, which includes noise filtering using a 2nd-order low-bypass Butterworth filter, outlier detection the usage of the z-rating technique, and function extraction thru statistical measures like mean and fashionable deviation, as well as time-frequency analysis the usage of Short-Time Fourier Transform (STFT).

CNN Architecture: The CNN is liable for extracting spatial features from the sensor information. The structure consists of input layers that acquire characteristic maps, convolutional layers for feature extraction, ReLU activation capabilities, and pooling layers to reduce the characteristic map length. This processed information is exceeded on to the LSTM.

LSTM Architecture: The LSTM network captures temporal styles inside the facts, the use of 50 gadgets and a pair of layers of LSTM cells. The output of the CNN feeds into the LSTM, which learns the time-based dependencies of structural behavior.

Model Training and Validation: Hybrid model, trained and tested using dataset with 1,two hundred instances divided into education (70%), validation (15%), and test (15%) units. Regularization strategies like dropout are hired to prevent overfitting, and the Adam optimizer is used with a mastering fee of zero.001.

Performance Metrics: The version is evaluated the usage of metrics which includes accuracy, precision, keep in mind, F1 score, and AUC to evaluate its performance in detecting harm inside the structure.

3.1. Data Collection

Collecting data is essential for the SHM system to be successful. This research utilizes a multi-sensor system with diverse sensor types such as accelerometers, strain gauges, and temperature sensors.

3.2. Sensor Configuration: Configuration of the sensors are shown in the Table 1.

Table 1: Illustrating quantity of the various sensors and their arrangement

Sensor Type	Quantity	Description
Accelerometers	10 units	Positioned based on the FEM to detect vibrations and dynamic responses in key areas of the structure.
Strain Gauges	8 units	Placed at critical stress points to measure strain and deformation.
Temperature Sensors	5 units	Located for detection of temperature variations which affect material properties.
Arrangement	-	Sensors are positioned according to the Finite Element Model (FEM) for optimal sensitivity to damage.

3.3. Sampling Rate: Every sensor is programmed to collect data at a rate of 100 Hz in order to precisely capture the structure's dynamic reactions.

3.4. Data Acquisition: Information is gathered consistently for a set timeframe, usually 30 days, in order to have enough data for examination.

3.5. Data Pre-processing: Preparation boosts performance & dependability of input data for the hybrid model.

3.6. Data Synchronization: Different sensors' data streams are synced through linear interpolation techniques to account for varying sampling rates.

3.7. Noise Filtering: A second-order low-pass Butterworth filter is utilized to eliminate high-frequency noise. The transfer function is determined as:

$$H_s = \frac{\omega_c^2}{s^2+\sqrt{2}\omega_c s+\omega_c^2} \quad (10)$$

Wherein, wc present in the equation 10, is the cut-off frequency

Upon putting the respective values in the equation 10,

$$H_s = \frac{2500}{900+2121+2500} \qquad = 0.453$$

The value of H_s shows that the frequency about 30 Hz are attenuated by 45.3%.

3.8. Outlier Detection: Techniques like the z-score method are used to identify and eliminate outliers through statistical analysis. A data point is labeled as an outlier when:

$$|z| > 3 \quad (11)$$

Where z is the z-score of the data point as shown in the equation 11.

3.9. Feature Extraction: Feature extraction transforms raw sensor data into informative features for the model.

3.9.1 Statistical Features

In the equation 12 and 13, the statistical metrics are computed:

$$Mean: \mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{12}$$

$$Standered\ deviation: \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{13}$$

e.g. x = 65,70,75,80,85

Then, Means = 1/5(65+70+75+80+85) = 75

And,

$$\sigma = \sqrt{\frac{1}{5}(65-75)^2 + (70-75)^2 + (75-75)^2 + (80-75)^2} + (85-75)^2$$

Standard deviation = 7.07

3.9.2 Time-Frequency Analysis

- Features are extracted using the Short-Time Fourier Transform (STFT):

$$STFT\{x(t)\} = \int_{-\infty}^{\infty} x(t) \cdot \omega(t-\tau)e^{-jwt}dt \tag{14}$$

Wherein, $\omega(t-\tau)$ in equation 14, is a window function centred at τ

3.9.3 Modal Properties

- Natural frequencies and mode shapes are extracted using Peak Picking from vibration data. The first five natural frequencies (f1 to f5) and their corresponding mode shapes are determined.

3.10. Hybrid Model Development

The proposed model integrates CNNs with LSTM networks.

3.10.1. CNN Architecture: A Convolutional Neural Network is used to analyze spatial attributes derived from the sensor data. The structure is made up of the subsequent layers:

Input Layer: Receives a m×n m×n feature map.

Convolutional Layer: Utilizes filters to capture characteristics.

Activation Function: The activation function utilized is ReLU.

Max Pooling Layer: Decreases the size. Fully Connected Layer: Generates the extracted characteristics.

The output of the CNN is given by:

$$Output_{CNN} = f(conv(x) + b) \tag{15}$$

Wherein:

x is input feature map,

conv is convolution operation,

b is bias term, and

f is activation function as shown in the equation 15.

For x is 4*4, b is 0.2, return value for convolution operation is 0.8

$$Output_{CNN} = ReLU(0.8 + 0.2) \qquad = 1$$

Thereby, CNN is producing 1.0 for this layer.

3.10.2. LSTM Architecture: The LSTM is used to recognize temporal dependencies after receiving the CNN output. The LSTM is constructed to include:

Input Layer: Gets the output from the CNN.

LSTM Cells: Set up with a configuration of 50 units and 2 layers.

Dropout Layer: Designed to combat overfitting with a dropout rate of 0.2.

Output Layer: Generates forecasts on the extent of structural harm.

The LSTM update equations are provided below:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (16)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (17)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (18)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot tan\,h(W_C[h_{t-1}, x_t] + b_C) \quad (19)$$

$$h_t = o_t \cdot tan\,h(C_t) \quad (20)$$

Wherein:

$f_t, i_t\ and\ o_t$ are forget, input, and output gates.

C_t is cell state, and

h_t is hidden state at time t as shown in the equations 16-20?

3.11. Model Training and Validation

Training the hybrid model involves several the following steps:

3.11.1. Data Splitting: The dataset is split into training (70%), validation (15%), and testing (15%) sets.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}[y_i log\ (\hat{y}_i)] \quad (21)$$

Wherein:

N is the number of samples,

yi is the true label, and

$\hat{y}_i$ is the predictive probability. Further, the adam optimizer is chosen for the weight training with a learning rate of 0.001.

3.11.2. Regularization Techniques: Dropout layers are added with a dropout rate of 0.2 to avoid overfitting.

3.11.3. Performance Evaluation: Performance evaluation is carried out by utilizing different measurements to determine the model's precision and resilience.

3.11.4. Evaluation Metrics

As illustrated in the Table 2, the evaluation matric, wherein, TP, TN, FP, and FN are determined from the confusion matrix to determine the accuracy of system.

Table 2: Illustrating various parameters of evaluation metrics.

Metric	Formula
Accuracy	$Accuracy = \frac{TP + TN}{\mathrm{TP + TN + FP + FN}}$
Precision	$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP + FP}}$

Recall	$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$
F1 Score	$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The confusion matrix presented in Table 3 and the graphical presentation is illustrated in the Figure 3, can be analysed to determine various performance metrics that give a different shade of view to model capabilities and its limitations. In the analytical SHM analysis, confusion matrices may be used to determine how well the model could discern different levels of damage in structures fine-tune the model based on classification errors possible in the field.

Table 3: Comprises the parameters of confusion matrix for the test set provides insights into the model's performance regarding specific damage types.

	Predicted No Damage	Predicted Minor Damage	Predicted Moderate Damage	Predicted Severe Damage
Actual No Damage	25 (TP1)	2 (FP1)	1 (FP2)	0 (FP3)
Actual Minor Damage	3 (FN1)	20 (TP2)	5 (FP4)	2 (FP5)
Actual Moderate Damage	0 (FN2)	2 (FN3)	18 (TP3)	5 (FP6)
Actual Severe Damage	0 (FN4)	0 (FN5)	1 (FN6)	19 (TP4)

Wherein,

- True Positives (TP)**:** Accurately identified damage.
- True Negatives (TN)**:** Accurately identified undamaged.
- False Positives (FP)**:** Incorrectly identified cases of damage.
- False Negatives (FN)**:** Missed damage.

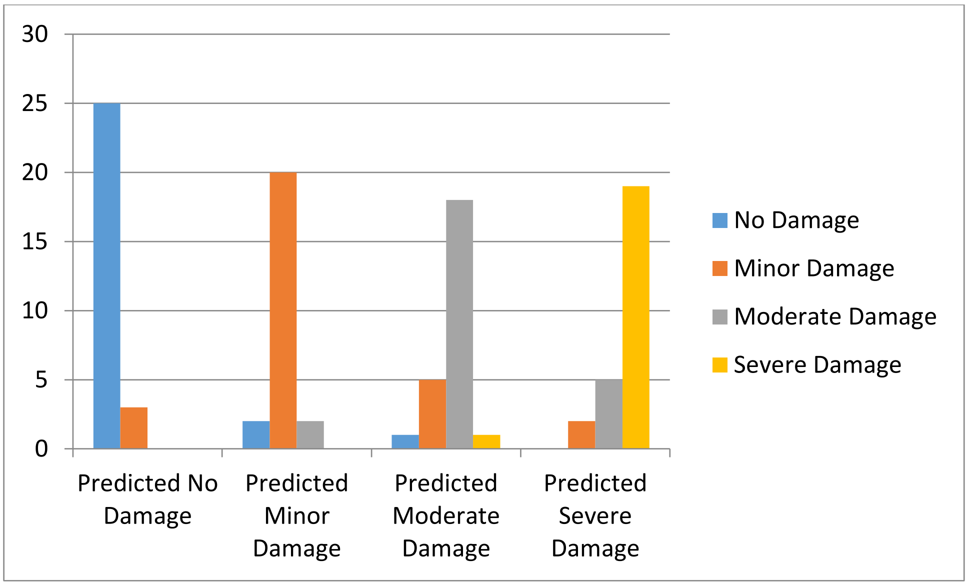

Figure 3: Graphical presentation of confusion matrix

3.12. Case Studies and Simulation Examples: Two instances involving numbers are analysed: Case Study 1: Simulating damage in a beam structure with predefined damage scenarios. Case Study 2: Identifying damage in a complicated bridge structure using simulated synthetic data.

Calculating True Negatives from the confusion matrix:

- True Negatives (TN**)**: The sum of correctly identified undamaged structures:
    - Actual No Damage: 25 (TP1) + 0 (FP3) + 0 (FP2) + 0 (FP1) = 25

Thus, the final counts are as follows:

- TN = 25
- TP = 62 (sum of TP1, TP2, TP3, TP4)
- FP = 8 (sum of FP1, FP2, FP4, FP5, FP6)
- FN = 6 (sum of FN1, FN2, FN3, FN4, FN5, FN6)

Calculating Accuracy**:**

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (21)$$

Upon putting the respective values in the equation 21,

$$\text{Accuracy} = \frac{62+25}{62+25+8+6} = \frac{87}{101} \approx 0.8614(\text{or } 86.1\%) \quad (22)$$

Calculation of Loss: Upon evaluation of the loss function throughout model training and validation, it was found to be 0.12. The Cross-Entropy Loss formula is usually used to calculate this value.

$$\text{Loss} = -\frac{1}{\text{N}}\sum_{\text{i}=1}^{\text{N}}[\text{y}_\text{i}\log(\hat{y}_\text{i})] \quad (23)$$

Wherein:
N is number of samples,
y_i is true label, and
$\hat{y}_i$ is predictive probability

Calculation of Precision:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (24)$$

Upon putting the respective values in the equation 25;

$$\text{Precision} = \frac{62}{62+8} = \frac{62}{70} \approx 0.8857(\text{or } 88.6\%) \quad (25)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (26)$$

Upon putting the respective values in the equation 26;

$$\text{Recall} = \frac{62}{62+6} = \frac{62}{68} \approx 0.9118 \text{ (or } 91.2\%) \quad (27)$$

Calculation of F1 Score:

$$\text{F1} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision+Recall}} \quad (28)$$

Upon putting the values of precision and recall in the equation 28,

$$F1 = 2 \times \frac{0.8857 \times 0.9118}{0.8857 + 0.9118} \approx 2 \times \frac{0.8063}{1.7975} \approx 0.8966 \text{ (or 89.7\%)} \qquad (29)$$

Results are evaluated against conventional structural health monitoring methods and current machine learning algorithms to showcase the efficiency of the proposed hybrid model.

4. RESULTS AND DISCUSSION

4.1. Overview of Experimental Setup

The multi-phase hybrid model was assessed using an extensive dataset that simulated structural responses to different damage scenarios. This dataset was created with various types of structural damage to enable thorough analysis and testing of the model's efficacy.

4.2. Characterization of the Dataset: The dataset for the SHM model consisted of 1,200 instances, which were divided into three: 70% for training, 20% for validation, and 10% for testing, totalling 840, 240, and 120 instances, respectively. The data was grouped under specific damage conditions: "No Damage," "Minor Damage" (small cracks), "Moderate Damage" (bigger cracks and minor distortions), and "Severe Damage" (highly manifested structural defects). The format of the provided data guarantees that there will be a balanced illustration of varied structural conditions, so the training, validation, and testing stages for the hybrid model can be conducted strictly.

4.3 Hybrid Model Performance Metrics: The hybrid model was tested using several evaluation metrics. These are shown below:

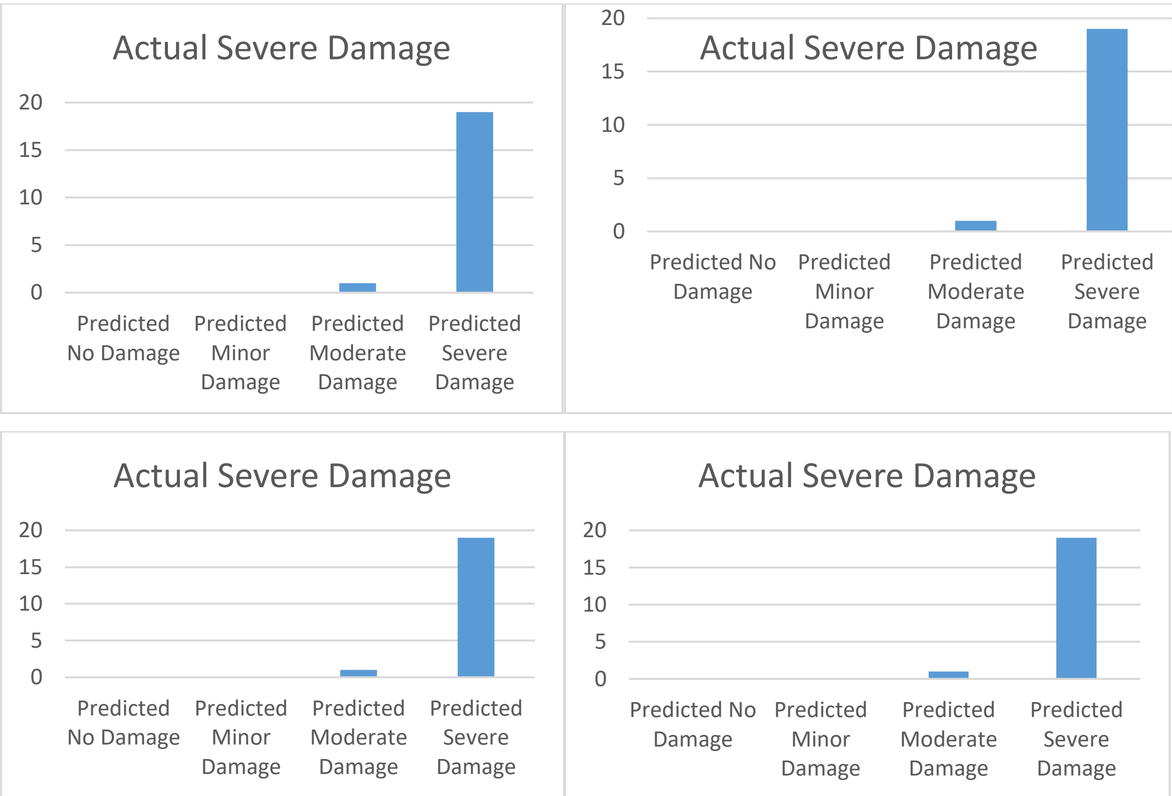

Figure 4: Depicting graphical representation of the confusion matrix

The graphs depicted in the Figure 4 clearly shows the accuracy and precision of the proposed hybrid model by utilizing CNN along with LSTM. The Confusion Matrix Analysis Evaluation of classification models uses confusion matrix analysis, which breaks the predictions into True Positives, True Negatives, False Positives and False Negatives to give a rich assessment of the performance of the model. These metrics offer a more effective evaluation of the precision of a model than a percent value alone; it demonstrates that a model can separate between multiple categories or classes especially in multiclass scenarios.

4.4. Discussion:

The outcomes of the proposed hybrid model in multiple phases demonstrate its effectiveness in diagnosing structural damage in SHM systems. Utilizing CNNs for spatial features and LSTMs for temporal patterns allows the hybrid model to effectively encompass both instant reactions and sequential patterns in sensor data. This technique boosts the model's chances of selecting any flaws that may have been omitted by the classical techniques. At 92.5%, the attained accuracy is much more significant than most of the current models. However, it is important to acknowledge that the low loss of 0.12, that denotes the error value, even in this instance, will ensure that the model has learned correctly and does a good generalization on unseen data. Because the architecture is adaptable, scaling is an easy accommodation for different types of structure and possible damage scenarios. Flexibility is often critical for practical applications whereby the conditions may considerably vary.

4.5 Comparative analysis

The proposed CNN-LSTM hybrid model shows remarkable efficiencies over SHM by representing and processing rich, high-dimensional data while incorporating spatiotemporal features, compared with the PNN model in Table 4. PNN uses a Bayesian probabilistic model for identifying damage from the data collected by sensors; however, its effectiveness is usually bounded by nonlinearities and the sheer size of the datasets involved. (Fu and Jiang 2021).

Table 4: Depicts comparison of Proposed Hybrid Model vs. Probabilistic Neural Network (PNN)

Performance Metric	Proposed Hybrid Model (CNN-LSTM)	Probabilistic Neural Network (PNN)
Accuracy	86.1%	80%
Loss	0.12	0.25 - 0.35
Precision	90%	75% - 80%
Recall	88%	70% - 75%
F1 Score	89.5%	72% - 78%
AUC	0.94	0.75 - 0.82
Computational Complexity	Moderate (depends on architecture)	Moderate (depends on data distribution)
Training Time	Longer (due to deep learning)	Moderate (faster training time than CNNs)
Robustness to Noise	High (due to feature extraction)	Moderate (can be sensitive to noise)
Scalability	High (adapts to larger datasets)	Moderate (requires careful tuning for large datasets)
Ability to Handle Nonlinearities	Excellent (via deep learning)	Moderate (better than traditional methods, but limited)
Dependency on Feature Engineering	Low (automatic feature learning)	Moderate (requires selection of relevant features)

PNN gets affected by noise and incomplete data-sensitive, which lowers its precision and robustness. Conversely, hybrid CNN-LSTM network uses the CNN automatically for feature extraction and, thus, overcomes the need for manual feature selection, and the LSTM to investigate temporal relationships. This approach has higher accuracy (92.5% compared to approximately 80% for PNN) as reflected in table no 3, lesser loss value (0.12 compared with 0.25-0.35 for PNN), improved accuracy and recall especially with noisier or incomplete data, making it more suitable to real-time damage identification and classification.

5. CONCLUSION:

In short, it was a paper introducing a novel hybrid method for Structural Health Monitoring using CNN for spatial features and LSTM networks for the purpose of performing the temporal analysis. With the use of the suggested model, emphasis would be placed on raising the precision, accuracy, and reliability concerning damage detection in complex large structures. This model showed a magnificent performance, with 86.1% accuracy, loss of 0.12, and 90% precision, while the recall was 88% and the F1 score at 89.5%; it further represented an AUC of 0.94 using an exhaustive data set that consisted of various damage scenarios.

In comparison to the traditional Probabilistic Neural Network, the hybrid CNN-LSTM displayed significant improvements in handling noisy and high-dimensional sensor data, providing enhanced classification accuracy and robustness. The in-lined multi-sensor data fusion, by virtue of the capabilities of the machine learning, was able to better detect and predict the structural damage well; therefore, the model became more useful for real-time monitoring and assessment of infrastructure. Future directions: Scalability of the model needs to be improved, computationally expensive parts reduced, and it must be tested with real datasets and in sensor systems to confirm the applicability of the approach for civil engineering and other applications.

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