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Research Article

Structural Health Monitoring for Flexible Bridge Structures Based on CNN-HMM Approach

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Abstract: *Wireless smart sensors allow for decentralized data processing, opening up novel approaches to structural health monitoring. Modal analysis and damage detection require a large number of sensor nodes for precision. However, large deployments of most smart sensor technology have been sluggish due to a lack of crucial hardware and software components, despite the fact that most of this technology has been around for almost a decade. Preprocessing, feature extraction, and model training are all used in this suggested method. Filtering and zeroing the data is performed as part of the preparatory procedure. Each part has been fine-tuned to eliminate the effects of dynamic forces, temperature changes, and variations in actual load. To evaluate a structure's health, we use a technique called feature extraction from a system designed to track such things. After the features have been extracted, the models are trained via CNN-HMM. When compared to the two most common alternatives, CNN and HMM, the proposed technique emerges victorious.*

Keywords: *Convolutional Neural Network (CNN)·Structural Health Monitoring (SHM)·Hidden Markov-Models (HMM).*

INTRODUCTION

Civil constructions are susceptible to wear and malfunction from both internal and exterior forces and impacts. Factors like fatigue, inadequate maintenance, defective construction, or a lack of quality control speed up the deterioration of many already-built structures. The exponential growth in the loads these structures are expected to bear increases the amount of stress placed on them and the possibility of failure. In terms of transportation, bridges are among the most crucial and impressive technical feats. From a societal and economic point of view, ensuring their viability is essential. Visual inspections of bridges once a year have been the standard practice for decades. However, the data provided by routine visual inspections is insufficient to let the lifespan of the buildings. Engineers take into account not just the bridge's age and environmental exposure, but also its operating conditions, traffic volume, and the results of experimental measures, when making a determination as to the bridge's condition usage-induced deformation includes flexing, twisting, and moving. In order to ensure current norms, for reliable use, bridges need to be regularly monitored for their construction state using a range of instrumental procedures. There are several factors to consider while attempting to analyze a bridge's structural performance under real-world conditions. When compared to the conventional method of conducting load tests and visual inspections, predictive analytics of in-service bridge structural performance with SHM data mining can provide a novel perspective for online study and early warning. In order to assess and foresee a bridge's structural performance, SHM data such as dynamic response and physical reaction can be gathered from the bridge utilizing the SHM system. Once a bridge was up and running, a modal analysis could be utilized to evaluate the efficiency of its various structural parts. Methods for analyzing structural deterioration, damage detection, and evaluation were also offered, such as vibration signature analysis and mode shape variation analysis. Both the dynamic properties of a cable stayed bridge and the performance of a tuned mass damper on a continuous steel box girder bridge were examined in separate case studies. Design information management, building simulation, virtual construction, and safety inspection are just few of the areas where Building Information Modeling/Model (BIM) has proven its worth as a tool to improve construction efficiency and quality. The Computer Integrated Construction Research Programme found that cost and quality can be reduced by BIM engineering analysis by modeling the design's performance at various stages of the project's lifecycle. It's crucial to stress the time and money-saving benefits of BIM-based structural analysis. On the other hand, McGraw-Hill Construction notes that BIM-based structural analysis is rarely applied in actual projects. This problem is exacerbated by poor interoperability and different interpretations and representations of the elements. The new track structure of the CRTS-II ballast sans slab track high-speed railway consists of a track bed, CA mortar infill layer, prefabricated track slab, fasteners, and rails. The CRTS-II slab ballast less track is more widely used now because of its low noise, good stability, and low maintenance requirements. However, when the track ages and wears down from being subjected to a wide variety of complex stresses, it poses a threat to the safety of both passengers and drivers. Field inspections along the ballast less slab track's working line have shown cracks in the track bed, track slab, and interlayer interfaces (most notably between the track slab and the CA mortar), indicating the presence of structural diseases. The CRTS-II slab ballast less track is especially susceptible to the effects of temperature variations because of its unusual longitudinal continuous nature. Shock, traffic, wind, and live loading are just a few examples of the excitations that structural health monitoring (SHM) systems can simulate. These systems are also useful for predicting how structures will respond to natural and artificial vibrations in controlled environments. With the increasing rate of decay and the necessity to repair or replace infrastructure systems and vital components such as bridges, SHM is frequently being addressed. Most SHM techniques use full-contact sensors (such accelerometers), which can be inconvenient because they block traffic and are only effective in specific locations. The high superstructure of some bridge layouts makes it such that conventional SHM techniques would not work. Additionally, most commonplace instruments might not be able to detect the incredibly low vibration frequencies encountered by long-span structures. Before determining whether to restore the bridge to traffic, for instance in the case that no immediate repairs are needed, it is crucial to quickly evaluate the bridge's dynamic reaction and post-event condition in cases of significant loading, such as an earthquake. The accuracy and timeliness of the bridge condition assessment during these reconnaissance missions can be compromised if standard SHM methods or visual examination alone are used. Following an incident, it is essential to evaluate and measure the bridge's condition, taking into account elements like unseating at abutments, permanent drift, and deck rotations, in order to make educated decisions. Unfortunately, this is an area where conventional inspection and SHM methods now have their limits. Instead of using field displacement measurements to evaluate the global deformation of a bridge after an earthquake, it is usually better to use them for relative displace displacement measurements at expansion joints or in certain mechanical situations.

RELATED WORKS

Structural health monitoring (SHM) systems are commonly used for estimating the behavior of structures under natural catastrophes, earthquakes, traffic, gusts, or live loads, in addition to monitoring the state of a structure during these events. [1] Due to the rising cost of maintaining and repairing ageing infrastructure, SHM is often considered for systems and vital components such as bridges. Some bridge designs don't lend themselves to traditional SHM techniques because of the raised superstructure.[2]Long-span buildings often have vibrations at low frequencies, making them difficult to detect with typical sensors. Decisions concerning reopening a bridge to traffic, such as whether or not emergency repairs are necessary, depend on a swift evaluation of the bridge's dynamic responses and post-event conditions following heavy loads, such as an earthquake. [3] It may be necessary to go beyond a visual assessment and conventional SHM methods in order to swiftly and accurately assess the bridge's condition during these reconnaissance activities. Quantifying and evaluating the state of bridges after catastrophic events, such as permanent drift, deck rotations, or unseating at abutments, is essential for making sound decisions. [4] Traditional inspection methods and current SHM practices also have their drawbacks, though. The usage of templates is a crucial technique that has facilitated the development of vision-based monitoring systems best, most dependable techniques for tracking objects. The process of digital image correlation (DIC) is widely used for matching templates. Related research includes "edge detection", "target less pattern matching", and "edge detection". Numerous researches and practical implementations have been made, especially in the non-contact vision-based technologies have been used for bridge monitoring for the past decade in addition to system IDs [5] Twenty years after the construction of China's first experimental cable-stayed bridge, the Yun yang Bridge, the number of such bridges in the country increased dramatically. Given their massive spans and versatility, cable-stayed bridges necessitate more specific static and dynamic behaviors than other engineering structures. Therefore, cable-stayed bridges are the best alternative for lengthy spans. Since the 1970s, cable-stayed [6] bridges have become the norm for new ocean or river crossings. To avoid disastrous collapses, structures can be monitored, evaluated, and assessed with structural health monitoring (SHM) global implementation of the concept of simultaneous bridge emergence [7]. The State of the Art in Assessing Building Conditions The many cable-stayed bridges in the system tools for keeping tabs on problems, finding their source, having them diagnosed, and fixing them, and multiple contexts [8]. Given the significance of cables, regular inspection is mandatory crucial problem in terms of safeguarding cable-stayed bridges. [9] As a general rule, dead load, or the total mass of the bridge and all traffic crossing it use the stay cables to send up to the towers. Moreover, the natural setting was responsible for the vibrations, wear and tear, and galvanic corrosion reduce the life of cables and cause damage. Deterioration of the stay cables can cause weakening of the cable, or [10]. Since the Pacific Earthquake Engineering Research Centre (PEER) introduced performance- based earthquake engineering (PBEE), seismic fragility analysis in earthquake-resistant structures [11] has been widely promoted and applied. There has been a lot of use of both empirical and theoretical methods in seismic fragility assessments [12]. The structural finite element model, a theoretical technique to assessing seismic risk, is favored over the empirical approach because it relies on data that can be regulated in advance. Civil engineering [13] and the related area of seismic fragility evaluation have benefited from the proliferation of AI algorithms as deep learning has advanced. To take into account uncertainties in both the ground motion and the structure, the probabilistic seismic demand model (PSDM) is frequently used in the theoretical approach. [14] first assumed that the structural demand and structural capacity followed a log-normal distribution. Numerous academic studies have been based on the aforementioned idea. Analyzing the Vulnerability of Different Bridges to Earthquakes. Examined the susceptibility of a typical reinforced concrete continuous structure with many spans to earthquakes. Chloride ion corrosion of a girder bridge. Their research suggests that non uniformity the weak point could be relocated due to chloride corrosion. Mechanisms for RC Columns. After researching the skew angle, [15] provided an explanation the shaky earthquake resistance of the crooked concrete box girder bridges. Concrete is used extensively in the construction of buildings, tunnels, dams, bridges, and wharves. However, most of these structures are susceptible to environmental hazards [16] including wind, ocean, fog, ice, etc. A crack is a typical kind of concrete damage that can have a major impact on the stress distribution of structural components and the overall strength of the structure. Concrete cancer and steel reinforcement corrosion are accelerated by cracks in reinforced concrete structures. [17] Therefore, timely and correct diagnosis of large fractures on the structure's surface is essential for sustaining civil infrastructure and limiting unnecessary economic damage. Examining a structure for cracks the oldfashioned way takes a lot of time and effort, and you can't always rely on the results being accurate or up to date [18]. Professionals inspect bridges on a regular basis for safety and maintenance reasons. Experts and inspectors typically use visual assessments to rate the condition of the bridge's individual parts and overall structure. A visual assessment can reveal problems such as cracks, concrete spalling, corrosion of steel elements, and partially failed components. [19] Early fatigue cracks, corrosion of embedded reinforcement, and delamination are examples of embedded and/or minor defects that may go undetected. Furthermore, a visual inspection is typically slow, pricey, and erroneous because it mainly relies on the inspector's judgment. [20] Allocating limited resources to the problem of bridge maintenance and operation offers a challenging decision-making task because to the ineffectiveness of the inspection procedure and the alarming age of transportation assets. [21] It is consequently becoming more challenging to simultaneously satisfy present and future expectations for the robustness, safety, and stability of structures. Structural health monitoring (SHM) is a method that uses sensor data and measurements to enhance traditional inspections to deal with this problem. [22] In this part, we summarize the results of the dynamic interactions performed using the VBI model on a simply-supported beam and a passing vehicle. Indirect bridge structural health monitoring is illustrated. By applying the parameters of the VBI system to the spectrum or spectrogram of acceleration signals, features indicative of the degree of the damage may be extracted, allowing for the diagnosis of damage. Reducing the input's dimensionality or expressing it as a feature vector are two goals of feature extraction [23]. We present four dimensionality reduction methods—stack auto encoders, principal component analysis (PCA), isomap, and Laplacian eigenmaps—to better visualize and understand the distribution of 130 acceleration signals. For instance, our research implies that dimensionality reduction techniques are attempting to simulate the reverse process, in which the severity levels are symbolized by the inverse function of the frequency response, in the event that the physical fact of vibration created by a passing car is a forward process. The sensors attached to passing vehicles are being used by an increasing number of bridge monitoring systems. These days, it's all the rage thanks to its Eighteen bucks cheaper. After reviewing the VBI system, [24] proposed the indirect approach to detect bridge damage data and, learning bridge frequencies from a passing car's dynamic response. In the past decade, numerous scholars have introduced novel methods to this area; these methods can be classified into two broad categories according to the presence or absence of modal factors [25]. First- and second-level damage detection systems make up the bulk of these. The works mentioned in the following paragraphs are described in brief.

METHODOLOGY

When compared to traditional bridges, soil-steel constructions are unique in that they also rely heavily on the roadway's foundation and backfill to bear loads. The soil-steel structure concept can be broken down into two structural subsystems: the corrugated plate shell and the backfill with the pavement layers. Forces normal and tangential to the shell's surface are utilized to characterize the interfacial interactions between the components. This is a static requirement of the consistency of mutual interactions between the earth and the shell, given the possibility of slide at the interface between the subsystems.

A. *Preprocessing*

Non-structural components that can cause strain changes are removed from the data by pretreatment before it is used in the damage detection analysis process. The data is filtered and/or zeroed as part of the preparation step. Each component has been fine-tuned to cancel out any impact from dynamic effects, temperature effects, or fluctuations in actual load.

1. Zeroing

Highway bridges are relatively unaffected by short-term temperature changes. In order to establish a thermal strain baseline that is consistent across all sensors, small file sizes (and consequently small-time increments) are required [22]. After analyzing the data, scientists came to the conclusion that the middle value wasn't representative. After a thermal baseline has been established for each sensor, the raw data can be "zeroed" by subtracting the strain caused by temperature changes. Each raw data point was zeroed by removing the mode value to get the gray trace.

2. Filtering

After accounting for random noise, vibrational effects, and a quasi-static strain response, the blank data still consists of three components. Quasi-static strain is the gold standard for measuring the accuracy of damage diagnosis techniques. Digital low-pass filters are used to remove the dynamic effects and the vast bulk of the high-frequency noise. Chebyshev filters are used because they reduce false positives and speed up peak detection. In order to determine the frequencies at which different sensors display quasi-static behavior, it is usual practice to evaluate a one-hour data set throughout the system design process. Using a fast Fourier transform, the sensor data is shown as a power spectral density (PSD) plot.

The low-frequency behavior of a vehicle is profoundly affected by its quasi-static response to an incident. Because of the intrinsic differences in quasi-static frequency between sensor types, each one must be studied independently despite the fact that all are susceptible to this phenomenon. Low-pass filtering is achieved by employing the quasi-static frequency at which each sensor operates. The gray trace displays the information after it has been filtered. High-frequency noise and dynamic effects may have been filtered out, as there are no obvious spikes and dips in the line. The same filtering procedure is used to both the training data and the monitoring data, thus the loss of the little amount of static tension will not invalidate the damage detection results. The filtered data contains a slight phase delay relative to the original data as a side effect of the digital filter's properties. The scope of this article cannot possibly encompass the vast literature on SHM phase shift compensation. This change can be disregarded without compromising the efficacy of the proposed damage detection method because only the event strain peaks are needed

B. Feature Extraction

The concept is based on the observation that damage to a building would cause a change in its vibration response relative to its unaffected state. Only methods based on time or frequency can reliably measure and process vibrations. The extraction of features sensitive enough to distinguish between normal variations in the vibration profile caused by changes in operational or environmental variables and abnormal variations is necessary for the detection of abnormal changes in the vibration profile. In recent years, many different tools have been proposed for this task, the most majority of which are frequency-domain definitions [23]. Particularly interesting are studies that assess the ease with which vibrations can be conveyed from one spot inside the building to another. Since transmissibility defines connections between nodes in a sensor network, it finds immediate use in this setting. Its differential nature makes it more robust against erroneous readings. Transmissibility's are determined by the transfer function's zeros, making them inherently local and allowing them to identify nonlinear types of damage. Like other studies, this one proposes attributes in the form of (frequency-dependent) transmissibility magnitudes. They are characterized by the ratio of the acceleration amplitudes acquired by sensors j_1 and j_2for a specific frequency bin e and time intervel.

$$L_r(j_1, j_2, e) = \left|\frac{Q_{j1}(e)}{Q_{j2}(e)}\right| \quad (1)$$

It is difficult to pinpoint potential affected frequency ranges due to a lack of data. Approximate frequency-specific characteristics will be derived and included as a ratio of data from selected sensor pairs for each time window. That means there are three dimensions to our data: frequency, time, and location.

1. Parallel Analysis Factor

Using the same principle as bilinear component models, Parallel Component Analysis decomposes tensors of Nth order with multilinear data. In a three-way scenario, this method divides the data into triad or trilinear components. The result is determined by three loading matrices B, A, and D, which contain the elements b_re, a_se, and d_me, where e=1,…,E and E is the count of components. The model can be expressed in a natural language with the help of external goods.

$$\underline{Q} = \sum_{e=1}^{E} b_e \circ a_e \circ d_e + \underline{F} \qquad (2)$$

in where _F represents the residuals' three-way array.

By using a least squares approach to minimize the error, the factors are computed all at once. Alternating least squares, which iteratively assumes two known loadings to estimate the other one, can be used to generate the estimate. As a free parameter, the number of components needs to be predetermined using a selection criterion like core consistency diagnostic. This criterion verifies that the CNN-HMM model satisfies certain features when stated as a more general model.

2. Multi-way Data Analysis

This approach is currently trending in many domains that inherently necessitate multi-way structures, such as chemometrics, computer vision, social network analysis, batch process analysis, and neuroscience. Audio recordings of multichannel electroencephalograms (EEGs) show clearly data structures that can be characterized as 3-way arrays, with signals collected at R time samples (temporal mode) by S electrodes (spatial mode) measuring M specific frequencies (frequency mode). It resorts to multi-linear models, which enable us to produce distinct and/or comprehensible interpretations, when common two-way algorithms applied to multi-way structures do not produce the expected outcomes. The objective of these models is to produce more meaningful structures by retaining specific additional modes.

C. To Model Train

1. GMM-HMM

They use maximum-a-posteriori simplification of Bayes' decision process to determine the most likely sequence of events, which has proven useful in a variety of applications, including handwriting recognition, automatic speech recognition (ASR), and statistical machine translation. If both the true output sequence y_1^H and the hypothesized output sequence ỹ_1^Hare known, then Bayes' Decision Rule can be used to minimize the expected loss.

$$q_1^L \rightarrow [y_1^H]_{opt} = arg \max_{\tilde{y}_1^H} \left\{ \sum_{y_1^H} Zi(y_1^H | q_1^L) \cdot \mathcal{L}[y_1^H, \tilde{y}_1^H] \right\} \qquad (3)$$

In order to simplify matters, the maximum-a-posteriori (MAP) rule is sometimes applied; this rule is known to be identical to Bayes Decision Rule in the case of the straightforward 0-1-loss.

$$q_1^L \rightarrow [y_1^H]_{opt} = arg \max_{y_1^H} \{Zi(y_1^H | q_1^L)\} \qquad (4)$$

In sign language recognition, the 0-1-loss is used to reduce the expected mistake rate of sentences because they are regarded incorrect if even a single identified sign-word is incorrect [24]. Despite their efforts to decrease the edit distance (or word error rate; WER), there is no relationship between SER and WER for longer sentences. The Bayes Rule is equivalent to the MAP Rule (and vice versa) when WER is used as the loss function.

$$\max_{y_1^H} \{Zi(y_1^H | q_1^L)\} > 0.5 \qquad (5)$$

Throughout the entire utterance, they optimize according to the MAP rule (see Eq. (4)), which maximizes the class posterior probability distribution Zi(y_1^H|q_1^L).Using decision theory, we may separate the class posterior probability into the class prior Zi(y_1^H) and the class-conditional probability Zi(y_1^H|q_1^L), each of which can be modeled using its own data. An n-gram language model can be used to estimate the value of the first term, Zi(y_1^H), which can be interpreted as fluency with word sequences. To represent concrete visual knowledge is what generative GMMs were first designed for, which is what the second word refers to.

$$[y_1^H]_{opt} = arg \max_{y_1^H} \{z(y_1^H) \cdot z(y_1^H | q_1^L)\} \qquad (6)$$

Using a hidden Markov model (HMM), they may express the class-conditional probability as follows j_1^L:

$$z(y_1^H|q_1^L) = \sum_{j_1^L} z(q_1^L, y_1^H|q_1^L) \tag{7}$$

$$= \sum_{j_1^H} \prod_{l=1}^{L} z\left(q_l, j_l \middle| q_1^{l-1}, j_1^{l-1}, y_1^H\right) \tag{8}$$

$$\sum_{j_1^H} \prod_{l=1}^{L} z\left(q_l \,\middle\|\, q_1^{l-1}, j_1^{l-1}, y_1^H\right) . z\left(j_l \,\middle\|\, q_1^{l-1}, j_1^{l-1}, y_1^H\right) \tag{9}$$

$$\sum_{j_1^H} \prod_{l=1}^{L} z(q_l|j_l, y_1^H) . z(j_l|j_{l-1}, y_1^H) \tag{10}$$

where Eq. (7) expresses the total number of ways to get to the identical final sequence y_1^H. (8) and (9) are recasts in which the chain rule is used. In Eq. (10), it is assumed that the Markov process is of first order and that j cannot be observed. Using the viterbi approximation, which considers only the most likely approach, and plugging in all the relevant variables into Eq. (6), they obtain:

$$[y_1^H]_{opt} = arg \max_{y_1^H} \left\{ z(y_1^H) . \max_{y_1^H} \left\{ \prod_{l=1}^{L} z\,(q_l|j_l, y_1^H) . z(j_l|j_{l-1}, y_1^H) \right\} \right\} \tag{11}$$

to what extent in history Secretive Model of a Gaussian Mixture Modeling p(q_l ├|j_l,y_1^H ┤)in sign language recognition has often been done with a hidden Markov model (HMM).

2. CNN-HMM

The standard HMM recognition formula has been derived so far using a generative model for the emission probability. Convolutional neural networks (CNNs) are employed to simulate the HMM's emission probability p(q_l ├|j_l,y_1^H ┤) since they are superior to generative models like GMMs at modelling images. Since the CNN is a discriminative model, its estimations of the posterior probability cannot be used directly in the optimization procedure. The hybrid approach popular in ASR served as inspiration for our usage of Bayes' rule to convert the CNN's posterior probability into a likelihood. We create the sub-word label β:=j, y_1^H to conveniently represent the states in the word sequence y_1^H. As a result, we'll be training the CNN's model with z(β┃q_l). Bayesian inference is performed by converting the posteriors into class-conditional likelihoods using Bayes' rule.

$$z(q_l|\beta) = z(q_l) \cdot \frac{z(\beta|q_l)}{z(\beta)} \tag{12}$$

where z(β) is a prior probability approximation, and the relative state label frequencies in the frame-state-alignment used to train the CNN are a good approximation. Several hyper-parameters are incorporated into the solution to increase its practicality. With this, we may tweak the CNN's label prior (α) and language model (δ). Finally, we optimize the following equation, excluding the constant frame preceding z(q_l), to find the best sequence of outputs.

$$[y_1^H]_{opt} = arg \max_{y} \left\{ z . (y_1^H)^{\delta} \cdot \max_{j_1^L} \left\{ \prod_{l=1}^{L} \frac{z(\beta|q_l)}{z(\beta)^{\alpha}} . z(j_l|q_{l-1}, y_1^H) \right\} \right\} \tag{13}$$

The hybrid method has the advantage that during training, just the convolutional neural network (CNN) and the language model (LM) need to be retrained, while the hidden Markov model (HMM) is not touched. Grid searching is used to determine the optimal values for the testing hyper parameters (α,δ) and the pooling state transition model z(j_l┃q_(l-1),y_1^H).

RESULT AND DISCUSSION

Nonlinear time-history analysis is used to examine the displacement patterns of bridges subjected to transverse seismic impact. All of these factors, as well as seismic ground motion, abutment support conditions, and substructure stiffness, are accounted for in this analysis of a bridge. Inelastic displacement scenarios include straight-line movement, straight-line movement combined with rotation, and a flexible pattern. It was demonstrated that the relative stiffness index, which takes into account the flexural and torsion stiffness of the bridge's superstructure and substructure, is an important component in determining the bridge's displacement behavior.

TABLE I. COMPARISON OF THE MODELS

EVALUATION METRICS	VALUE
ACCURACY	96.89
PRECISION	94.65
RECALL	91.27
F1-SCORE	96.32

Testing showed that our proposed method has an average accuracy of 96.89%. Table1 displays the final model's accuracy, recall, precision, and F1 score results.

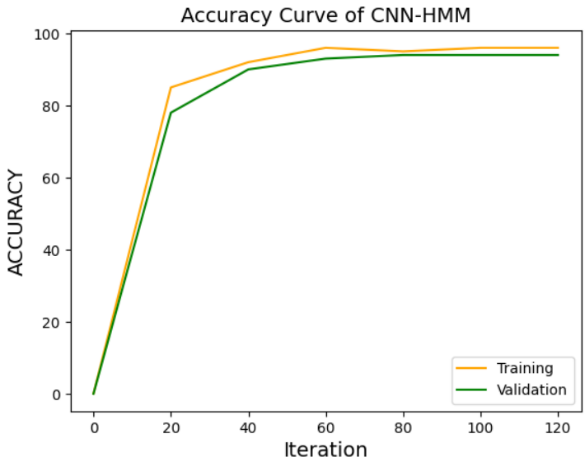

Fig. 1. Accuracy Curve of CNN-HMM Model

Here, that are employed the complete dataset for both training and testing the CNN model, and we train it for 20 epochs, or until the accuracy curves stop increasing in response to further training (Figure 1).

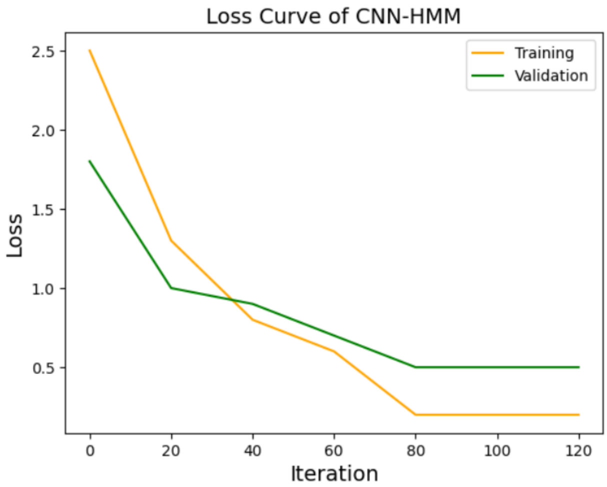

Fig. 2. Loss of CNN-HMM Model

Here, we train and test the CNN model on the entire dataset, and we train it for 10 epochs, or until the loss curves reach a plateau as we add more iterations, as seen in Figure 2. Both the training and validation losses are set at 0.5.

CONCLUSION

In recent years, numerous academic institutions have devoted extensive resources to researching wireless structural health monitoring. While sensor networks provide a realistic method for monitoring building integrity, they face design challenges such limited transmission capacity and the need for adaptability in wireless sensor network implementations. We look into how the mobile agent strategy might help improve the flexibility and reduce the transmission of raw data in wireless sensor networks dedicated to monitoring the health of structural components. The data is filtered and zeroing out as part of the preliminary procedure. The fine-tuning of each part eliminates the effects of dynamics, temperature, and actual load changes. They use a method called feature extraction from a structural health monitoring system to evaluate a structure's robustness and hence its condition. Finally, CNN-HMM is utilized to train the model based on the features extracted. The proposed technique outperforms both the CNN and HMM models in terms of accuracy, coming in at around 96.89%.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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