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Intelligent Structural Health Monitoring and Risk Assessment of Bridges using optimized Machine Learning algorithm

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ABSTRACT: Bridges are strong elements of transportation pattern, and their structural health is paramount for public safety and economic stability. Traditional structural health monitoring (SHM) techniques often rely on manual inspections and periodic assessments, making it challenging to detect hidden structural issues in a timely manner. This paper exhibits an innovative method to enhance the reliability and efficiency of SHM through the integration of machine learning algorithms, specifically CatBoost and Artificial Neural Networks (ANN). Firstly, the RDD2022 dataset, specifically curated for bridge damage detection, is utilized to provide a rich source of bridge crack images. To enhance the effectiveness of damage detection, a critical step is featuring selection, which reduces the dimensionality of the data while preserving crucial information. The Cuckoo Search Algorithm, known for its optimization capabilities, is employed to identify the most relevant features, thereby improving the efficiency of the subsequent classification process. The ANN model is fine-tuned using hyperparameter optimization techniques to ensure robust and precise predictions. The core of this approach lies in the fusion of CatBoost, a gradient boosting machine learning algorithm, and an Artificial Neural Network (ANN). The Hybrid CatBoost-ANN classifier synergizes the strengths of both algorithms, combining the interpretability of CatBoost with the pattern recognition capabilities of ANNs. This fusion yields a robust and highly accurate model for damage classification in bridges and Risk identification, capable of handling complex and diverse datasets. Experimental outcomes reveal that the proposed method outperforms existing systems in bridge damage detection, achieving superior accuracy of 99% and reducing false positives.

KEYWORDS: Hybrid CatBoost-ANN classifier; Cuckoo Search Algorithm; SHM; Bridge damage detection; CatBoost; Machine Learning Algorithm;

I. INTRODUCTION

Bridges are amazing works of engineering that have been essential to human civilisation for many years. These engineering wonders bridge natural barriers like rivers, canyons, and valleys to connect people, places, and economies [1]. Bridges are lifelines that make it easier to transfer people, things, and ideas. They also help communities and countries grow and thrive [2]. Over time, bridges have progressed from being straightforward wooden constructions to intricate and visually beautiful designs built from a range of materials, including stone, iron, steel, concrete, and even cutting-edge composites [3]. They can take on a variety of shapes, from modest footbridges in isolated settlements to tall suspension bridges connecting thriving metropolises. Each bridge serves as a symbol of human creativity, engineering skill, and the capacity to overcome obstacles presented by the terrain and environment [4]. Safety, lifespan, and operational effectiveness of essential transportation infrastructure are all ensured through structural health monitoring (SHM) and risk assessment of bridges [5]. In order to preserve public safety and optimize resource allocation, SHM delivers real-time or periodic data on a bridge's status. This enables early identification of possible problems and informed repair choices. By measuring risks and their effects, risk assessment supports SHM by directing proactive actions to improve bridge resilience against hazards like natural catastrophes. When used in concert, these techniques not only safeguard financial investments, increase bridge lifespans, and reduce environmental effect, but they also sustain continuous economic activity by averting expensive interruptions [6].

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There are many different causes of bridge deterioration, and each one presents particular difficulties and threats to the structural integrity. The normal aging and wear process is one prevalent reason. Bridges are continually used and exposed to the weather over time, which can cause corrosion, erosion, and structural degradation [7]. Furthermore, severe traffic loads, particularly those caused by large and frequent truck movements, can put a great deal of strain on the bridge's structural elements, leading to fractures, deformations, and fatigue. Natural calamities like hurricanes, floods, and earthquakes may also wreak havoc on bridges, resulting in abrupt and serious damage. Inadequate upkeep and inspections can make these problems worse by letting small faults grow into serious structural difficulties. Additionally, during the initial building of the bridge, mistakes in design and construction might result in structural weaknesses that eventually cause damage [8]. Finally, when the bridge's structural elements experience repeated stress cycles, material fatigue may develop, increasing the risk of fractures and eventual failure. Regular inspections, maintenance, and consideration of these aspects are necessary to guarantee the durability and safety of bridges. In the past, visual inspections carried out by qualified engineers and inspectors have been the mainstay of bridge damage identification. Experts physically evaluate the bridge's structural components during these inspections, searching for any obvious symptoms of degradation such cracks, rust, corrosion, deformations, and odd wear patterns [9]. To evaluate the integrity of crucial components like welds and support structures, they may also utilize analysis approaches like ultrasonic testing or magnetic particle testing. To evaluate the bridge's performance under various load circumstances, load testing may also be used. They are labor-intensive, time-consuming, and prone to human mistake. They could also miss harm that is concealed or in the early stages. There is an increasing tendency to use cutting-edge tools as structural health monitoring systems as technology develops. By enabling continuous real-time monitoring and data collecting, this invention lessens the need for frequent, expensive manual inspections while providing a more thorough and effective method of identifying and evaluating bridge problems [10].

structural health monitoring procedure that produces trustworthy information on a structure's current state and efficiency, that is referred by the general term "SHM." The physical condition and strength of the bridges must be captured to accurately diagnose and track bridge degradation [11]. A strategy for identifying structural degradation over a long period of time is SHM, which employs a series of continuous measuring sensors. The use of SHM equipment for tracking bridges has been the subject of several important research, the results of which have been provided [12]. In additionally collecting and gathering data from bridges, SHM is also able to assess, analyze, and forecast the data in order to decide what steps should be taken to increase and improve the strength and lifetime of bridges. Diagnosis and prognostic are the two broad groups into which SHM may be divided. Utilizing diagnostic tools, flaws, their locations, and the extent of their propagation are identified [13]. Prognostication, in contrast, takes use of testing findings to predict the amount of time that structure will remain standing. A brief description of the operation monitoring process for bridges installed by an SHM technology is shown in Figure 1.

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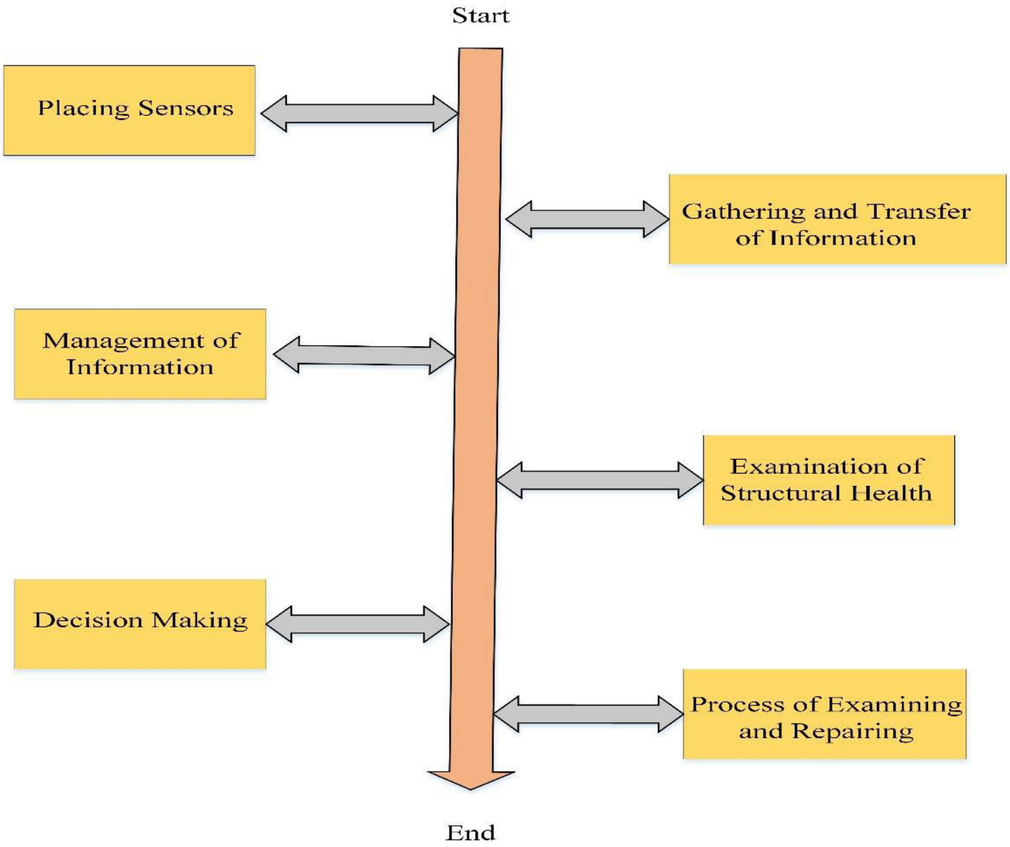

Fig.1.Process involved in SHM.

The hybrid optimized CatBoost-ANN methodology proposed in this study plays a pivotal role in this context. By combining advanced machine learning techniques with image processing and feature selection, it offers a powerful tool for automatically and accurately classifying bridge damage. This not only aids in early damage detection but also supports risk assessment by providing valuable data for decision-making. Ultimately, the methodology enhances bridge safety, extends their service life, and contributes to the overall resilience of transportation infrastructure. The key contributions of this research are as follows:

- The introduction of the RDD2022 dataset, an extension of RDD-2019, with a significantly larger number of high-resolution images collected from multiple countries, enhancing dataset diversity and size.
- The development of a robust two-step pre-processing pipeline that includes the application of an anisotropic diffusion filter (ADF) and a Hann mean filter (ADHF). This pipeline effectively reduces noise, preserves important structural details, and enhances image quality, crucial for accurate damage detection.
- The use of Otsu thresholding for image segmentation, a vital step in separating damaged areas from the road surface, simplifying subsequent analysis, and supporting informed decision-making for bridge maintenance.
- The utilization of the Grey Level Cooccurrence Matrix (GLCM) technique for feature extraction, capturing essential textural characteristics such as Energy, Entropy, Contrast, Homogeneity, and Correlation from bridge images.
- The application of the Cuckoo Search Algorithm for optimized feature selection, addressing computational complexity and overfitting issues while retaining important image features for classification.
- The development of a powerful hybrid classification model that combines CatBoost and Artificial Neural Networks (ANN) to accurately classify bridge images based on their damage status. This model not only

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enhances early damage detection but also supports risk assessment and decision-making for bridge maintenance.

- The comprehensive evaluation of the hybrid model's performance using metrics guaranteeing its trustworthiness and effectiveness in real-world bridge damage classification scenarios.

These contributions collectively offer a holistic and effective solution for bridge damage detection, classification, and risk assessment, ultimately contributing to the safety and maintenance of critical infrastructure worldwide.The leftover portion of this work is organised as follows: Sector 2 contains comparable work as well as a thorough examination of them. Section 3 contains information about the problem statement. The Optimized CatBoost-ANN architectures are discussed in detail in Section 4. In Chapter 5, the outcomes of the experiments are presented and examined, and a full comparison of the suggested strategy to current best practises is given. portion 6, the final portion, is where the paper is completed.

II. RELATED WORKS

The roadway security and longevity of highways are significantly impacted by deterioration to the concrete on the bridge surface. Ni et al.[14] founded a three-stage recognition technique in the you-only-look-once version 7 (YOLOv7) networking and the updated LaneNet was presented to attain damage identification and localisation of bridges platform. Five classifications for damage were acquired in phase 1 after the Road Damage Dataset 2022 (RDD2022) was cleaned and used to train the YOLOv7 model. Stage 2 involved pruning the LaneNet model to keep the semantic splitting component while using the VGG16 system as an encoding to produce roadway pictures. The lane area was determined in phase 3 by post-processing the binary lane line pictures using a suggested image processing technique. The concluded roadway damage classifications and lane localisation were determined using the damage-related values from the initial stage. The RDD2022 dataset was used to analyze and examine the suggested methodology. In comparison to previous algorithms in the YOLO series, the YOLOv7's average accuracy on the extracted RDD2022 dataset achieves 0.663, according to the findings. An issue is that training YOLOv7 and LaneNet frequently requires a lot of processing power and resources.

Drones use a wireless channel to transmit the data they have gathered to the server. However, the methods that have been created are extremely complicated, labor-intensive, and bandwidth-intensive. Kumar et al.[15] employs the edge computing approach to present a real-time multi-drone hazard detecting systems for high-rise buildings utilizing one of the latest YOLO-v3. The suggested system deploys on Pixhawk's electronics based on standards available access hexacopter drone and runs YOLO-v3 via the Jetson-TX2 equipment system. If damaged is seen the Jetson-TX2 on-board, after the process, delivers only the data associated with the harm to the server located on the surface via Wi-Fi. On a dataset of 800 images of various forms of damage, gathered from various CSIR-CEERI, Pilani structures, suggested method is assessed. The updated YOLO-v3 classifier is trained and tested using human annotated images. The conclusion is that the suggested method performs consistently with a precision of 94.24% and can analyze a picture in 0.033 seconds. Due to the approach's quick processing, one disadvantage is that it can make it impossible to preserve images of a few broken bounding boxes, which might prevent further research.

Long-span bridges' safety has been thoroughly ensured by SHM devices. Big data features are clearly visible in the large-scale structure reaction and loading data collected from multiple sensors. The impacts of sensory-based processing and information exchange are, however, inherently constrained by major "data island" issues that plague traditional SHM methods. There is a high demand for a universal bridge SHM conceptual presentation paradigm. Using Semantic Web methods, Li et al.[16] provides a unique model known as the Bridge Structure and Health Monitoring (BSHM) concept to allow very fine description of bridge constructions, SHM systems, sensors, and sensory data from many viewpoints. To show the utility, a bridge SHM large data is deployed. The study emphasizes the importance of additional investigation and testing of the integrated application of massive based on data and model-based techniques for bridge deterioration prediction.

Nazar et al.[17] proposes a new damage to structures detection technique that employs smartphone tracking of magnetic field strength fluctuations. Steel plates are subjected to laboratory and numerical examinations to validate the efficacy of the suggested method. Steel plates are subjected to a variety of damage conditions. Then, a mobile device's magnetic sensor is employed to quantify magnetic flux variations caused by damage progression. The physical and

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computational findings coincide quite well. According to the findings, the strength of the magnetic field rises as the damage develops. Furthermore, when the smartphone's spacing towards the steel plate base grows, the accuracy of damage identification decreases. One disadvantage of this study is that it focuses on detecting only a few pre-defined fractures. Future studies can solve this issue by examining many fractures in various directions.

Shang et al.[18] provides a damage identification technique built on deep convolutional denoising autoencoder that receives multifaceted cross-correlation values as input. The technique seeks to derive damage characteristics from unaffected field observations while accounting for noise and thermal uncertainty. Cross-correlation values for vibration information are initially estimated as fundamental features in the proposed approach; then a deep convolutional denoising autoencoder is constructed for reassembling cross-correlation operate using their noise-corrupted forms in order to derive needed features; and at last, rapidly ranked moving standard control graphs are built for such characteristics in order to identify smaller damage to the structure. A computational simple sustained beam version and a realistic continual beam designs are used to assess the method. By displaying feature translates of convolutional components in the encoder, the method of autoencoder for acquiring degradation features is analyzed. It has been shown that those layers make crude calculations of modal qualities and save damage data as the overall pattern of these qualities in numerous additional frequency bands. The issue of possible redundancy in damage data stored by distinct neurons in the blockage layer implies that more research and refinement are needed to eliminate this kind of redundancy, which might influence damage detection accuracy.

Ma et al. [19] presented in this work relies on the Variational Auto-encoder (VAE), which belongs to the most prominent productive models in uncontrolled deep learning. VAE is utilized in this research to process structural responses, which lowers multidimensional data to low-dimensional characteristic space and then recovers the actual data using its low-dimensional interpretations. Because of this framework, the VAE is forced to learn the fundamental features concealed underneath the complicated data. Using VAE to the damage identification job of a bridge under driving vehicle. Both computational modeling and practical findings show that the suggested technique can reliably identify physical damages. instead of the structural component model or historical information, this technique evaluates the observed reactions of the structure instantly. It is a data-driven technique without a baseline that is ideal for real-world engineering applications in SHM. The dependence on training data of an individual movable load, which does not completely depict the intricacies of real-world structural settings and loads, is one disadvantage of this research.

III. PROBLEM STATEMENT

The existing works revolves around the need to enhance and streamline the detection and assessment of structural damage in various engineering applications. Traditional methods of damage detection often require time-consuming manual inspections and may not adequately address the complexities of real-world conditions. Therefore, there is a demand for more efficient and accurate techniques that can reliably identify structural damage and its extent. While the proposed methods in these studies, including deep learning models, magnetic field intensity monitoring, and semantic representation models, show promise in improving damage detection, they each come with their own limitations. These limitations include computational resource demands, potential data loss due to rapid processing [16], the need for specific training data [17], and restricted applicability to certain types of structural loads and environments. Addressing these limitations is done by Optimised CatBoost - Artificial Neural Network (ANN) in structural health monitoring and ensuring the safety and longevity of critical infrastructure.

IV. HYBRID OPTIMIZED CATBOOST-ANN METHODOLOGY

In this study, the RDD2022 dataset is introduced for bridge damage detection, expanding upon the RDD-2019 dataset by including data from multiple countries. The dataset contains 26,620 high-resolution images categorized into four damage types. To prepare the images for analysis, a two-step pre-processing pipeline is applied. First, an anisotropic diffusion filter (ADF) is employed to reduce noise and enhance image quality while preserving edges and structures. Next, a Hann mean filter (ADHF) is utilized to further smooth the images and reduce fluctuations. Subsequently, Otsu thresholding is used for image segmentation, effectively separating damaged areas from the bridge surface. Feature extraction is performed using the Grey Level Cooccurrence Matrix (GLCM) technique, extracting textural characteristics such as Energy, Entropy, Contrast, Homogeneity, and Correlation. To optimize feature selection, the Cuckoo Search Algorithm is applied. Finally, a hybrid classification model combining CatBoost and Artificial Neural

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Networks (ANN) is developed. The dataset is split into training, validation, and testing subdivisions, and the hybrid model is trained to classify bridge images based on damage status. This model's output provides damage classification labels and is evaluated using various metrics. The resulting hybrid CatBoost-ANN model offers an accurate and reliable solution for bridge damage classification, contributing to infrastructure maintenance and safety. The proposed method is shown in fig.2.

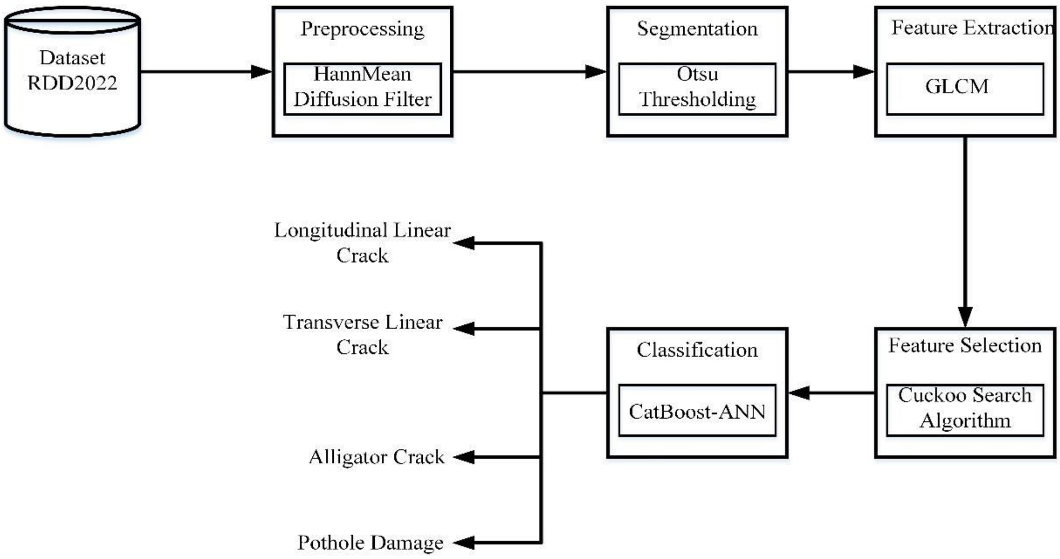

Fig.2. Hybrid Optimized CatBoost-ANN Methodology.

4.1 Dataset Collection

The RDD2022 dataset is an extensive source of data developed for detecting bridge deterioration. It contains a wide range of data, including high-resolution photographs, data from sensors, and construction information on numerous bridges. The suggested dataset expands on the recently released RDD-2019 dataset. It should be mentioned that the bridge damage information in the Road Damage Dataset 2018 and 2019 are limited to images taken from a single nation, Japan. However, the dataset offered in this study takes into account data from several nations. The following are the key points of distinction.

1. The overall number of images has been raised to 26620, about triple the current 2018 dataset.

2. New images were obtained from India as well as the Czech Republic (primarily from Slovakia) to diversify the data and train strong algorithms.

3. Unlike earlier forms, this dataset only analyzes four types of damage, namely cracks and potholes, notably D00, D10, D20, and D40. It should be noted that the criteria for evaluating road marking degradation, including Crosswalk and White Line Blur, vary greatly among nations. As a result, these characteristics were removed from the study in order to train generic models that may be used to monitor bridge situations in multiple countries. The damage types and criteria adopted for this dataset are exposed in Table 1.80% of the images were utilized for training and 20% for testing [20].

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Table 1. The RDD2022 dataset

Damage Type	Class Name
Longitudinal linear Crack	D00
Transverse linear Crack	D10
Alligator Crack	D20
Pothole damage	D40

4.2 Pre-processing with Hann Mean Diffusion Filter

To decrease noise, apply the diffusion filter to the RDD2022-generated bridge damage photos. As a result, a denoised image with maintained edges and structures will be produced. It is an iterative technique for recovering image intensities. The anisotropic diffusion filter outperforms all previous active filtering algorithms, including the gabor filter, gaussian filter, and so on. Edge-stopping functions are used to accomplish this. The anisotropic diffusion filter, abbreviated as ADF, is a sort of repeating algorithm that, in its most basic version, simulates the diffusion process as given in Eq. 1.

$$Y_i^{t+1} \approx Y_i^t + \frac{\lambda}{|\eta_i|} \sum_{p \epsilon \eta_i} y\left(\left|\nabla Y_{i,p}^t\right|, \gamma\right) \nabla Y_{i,p}^t \quad (1)$$

Where, Y_i^t represents the pixel's intensity in picture i at time t, λ represents the indicator of diffusion rate, γ represents the positive number for the smoothing constant, η_i represents the group of i's adjacent pixels, $y(.)$ represents the ESF (Edge stopping function),

Apply the Hann mean filter on the denoised image from the previous step. This filter smoothes the image even more and minimizes tiny fluctuations, resulting in better image quality. It works by substituting the rate of each pixel in the input images with the mean value of the pixels adjacent. Diffusion that is anisotropic The Hann mean filter (ADHF) reduces noise first, then performs controlled smoothing to improve image visual quality without losing crucial information is given in Eq.2.

$$ADHF = \left[\left(0.5 - 0.5.\cos\left(\frac{2\pi n}{N-1}\right)\right)\right] \times \left[\frac{1}{n \times n} \sum_{i=\frac{n}{2}}^{\frac{n}{2}} \sum_{j=\frac{n}{2}}^{\frac{n}{2}} Y_{i-j}(u+i', v+j')\right] \quad (2)$$

Where, n is the length of the window, $Y_{i-j}(u+i', v+j')$ denotes the intensity value of the original picture at the pixel location, and K denotes the dimensions of the rectangle or square kernel, which should be an odd integer (e.g., 3, 5, 7, etc.). The average value is computed by adding all of the intensity values within the kernel and dividing the total by the number of pixels within the kernel (n$\times n$). This average value replaces the previous pixel value in the mean-filtered image.

4.3 Otsu Threshold Segmentation

Otsu thresholding is a robust picture segmentation approach that is useful in a variety of applications, including road damage segmentation. By calculating an optimum threshold value to separate foreground from background, this approach is particularly good at detecting objects or regions of interest within an image. Otsu thresholding can efficiently differentiate damaged areas from the undamaged road surface in the context of road damage assessment. Otsu's method automatically selects the threshold that optimizes the variance between the two classes by examining pixel intensity values, allowing for the exact demarcation of road damage features such as cracks, potholes, or other sorts of deterioration. This method simplifies future analysis and enables informed decision-making for road maintenance and repair activities, assisting authorities in efficiently prioritizing and addressing locations in need of attention. Thus, otsu thresholding is a vital tool in the larger goal of ensuring safe and well-maintained road infrastructure.
Otsu's thresholding approach determines the best threshold value by maximizing the variation between two image classes (foreground and background). The threshold value is represented by the letter t.
The Eq.3 for Otsu's thresholding:

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$$T_{otsu} = \arg max_t[\sigma_b^2(t) \cdot \sigma_f^2(t)] \tag{3}$$

Where: T_{otsu} is the optimal threshold value. $argmax_t$ signifies the threshold value t that maximizes the following expression. $\sigma_b^2(t)$ is the variance of the pixel intensities in the background class for threshold t. $\sigma_f^2(t)$ is the variance of the pixel intensities in the foreground (object) class for threshold t. These variances and their product for various threshold values are calculated then the threshold value that maximizes this product is selected, which effectively separates the foreground from the background in the image.

4.4 Feature Extraction using GLCM

Feature extraction entails gathering information in order to bring down the number of resources necessary. The Grey Level Cooccurrence Matrix (GLCM) approach is employed in this study's feature extraction to extract texture-specific characteristics. Textural features extraction provides information about the physical structure of the surface and its relationship to its surroundings. Angular second moment (ASM), Contrast, Homogeneity, and Correlation are the texture-based characteristic metrics used in this study. The(x, y) th element is represented by the normalized Gray-Level Co Occurrence Matrix's m_{xy} item.

The energy state, also known as the angular second moment (ASM), has a high pixel count but a low grayscale value. The Energy determines consistent behavior in the GLCM by summing squared values. The energy units range from 0 to 1. The energy required for a steady image is 1. According to general Eq. 4,

$$Energy(E) = \sum_{x,y=0}^{N-1} m^2\,(x, y) \tag{4}$$

Entropy is a unit of measurement for heat's gradual decay of strength. The entropy value stated in Eq.5 is as follows:

$$Entropy = \sum_{x,y}(x, y)^2 \ln(m(x, y)) \tag{5}$$

Contrast can be used to determine the frequency distribution of a picture as well as the differences between a number of GLCM moments. The contrast throughout the entire image is used to identify how closely neighboring pixels are to one another. If the image is constant, the contrast value is 0. According to Eq. 6, the image's contrast solution is,

$$Contrast = \sum_{x,y=0}^{N-1}(x, y)^2\, m(x, y) \tag{6}$$

Correlation is the process of combining multiple pixels, and its values vary from -1 to 1. Correlation (COR) is a mathematical notion (Eq. 7) that describes the linear relationship between grayscale and image.

$$Correlation = \sum_{x,y=0}^{N-1} m(x, y)\left(\frac{(x-\mu)(y-\mu)}{\sigma^2}\right) \tag{7}$$

An inverse difference moment (IDM) is also known as homogeneity. This explains the pixels' resemblance. The homogeneity ranges from 0 to 1. The diagonally GLCM has a homogeneity ratio of one, as expressed in Eq. (8).

$$IDM = \sum_{x,y=0}^{N-1} \frac{m^2(x,y)}{[1+(y-x)^2]} \tag{8}$$

The mean value and variance of GLCM pixels are represented by μ and σ, respectively. The size of this feature extraction approach raises a number of concerns, including processing difficulties, complexity, and a substantial amount of memory waste, which complicates the classification process even if the characteristics are required for extraction. Furthermore, the extraction process produces low accuracy due to over-fitting issues caused by having too many features, which are minimized utilizing the cuckoo search feature selection approach [21].

4.5 Optimizing Feature Selection with the Cuckoo Search Algorithm

The CSA has influenced the cuckoo bird's propensity of laying its eggs in the nests of another birds. The host bird discovers the foreign eggs with a P_a probability and either discards them or rejects the nest. Each egg positioned in the nest represents a CSA solution. Placing the eggs in securer nests (i.e., where the host bird will not find the cuckoo's eggs) may be a preferable strategy. Cuckoos have been searching for more effective remedies for generations. Each nest denotes a collection of solutions to the challenge, with each egg representing a separate answer. CSA is frequently based on three principles:

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1) Individually cuckoo only puts one egg at a time and places it among the nests.

2) The nests with the best eggs or the finest solutions are used for the next group.

3) Nests are always available, and the host bird has a P_e chance of seeing each cuckoo egg.

The first stage in CSA is to randomly seed a population in n host nests. Each host nest contains one cuckoo egg. Several of these eggs may hatch into mature cuckoos. With a probability of P_e, the host bird determines and destroys any other eggs. Cuckoos are drawn to specific locations because the number of eggs that hatch indicates the quality of the nest within that site. The purpose of the cuckoo algorithm is to maximize a parameter that determines the situation in which the most eggs are rescued. Cuckoos should equalize global random walk as well as local motion to improve finding and devise a better strategy for shifting to the area with the best nests. The global random walk is mathematically represented by Eq.9. [22].

$$P_j^{t+1} = P_j^t + \beta \otimes Lavy(v) \tag{9}$$

Where P_j^{t+1} and P_j^t denote the j[th] cuckoo's future and present locations, accordingly. The step size that is often regarded as one is indicated by β > 0. An entry-wise multiplication is the ⊗. The Levy distributions with a rate of v is called $Lavy(v)$. Equation (2) can be modified as in Eq. (10)

$$P_j^{t+1} = P_j^t + d_p \otimes (P_{best}^t - P_j^t) \tag{10}$$

where the vector d_p contains random values distributed uniformly in the range [0, 1] and is known as the deviation parameter. Two cuckoos with indexes of k and l are randomly chosen from all other cuckoos to simulate the local random motion of cuckoo j, and the cuckoo's subsequent position is determined by equation 11.

$$P_j^{t+1} = P_j^t + \beta \otimes H(P_e - \gamma) \otimes (P_k^t - P_l^t) \tag{11}$$

Where, γ is a randomly chosen value produced using the normal distribution.

4.6 Classification and Severity of Damage using Hybrid CatBoost -ANN

4.6.1 CatBoost overview

Catboost is a gradient boosting decision tree (GBDT) that handles categorical variables and has high accuracy. It is a tree-based base learner with categorical and boosting properties. Gradient boosting is used in decision trees that take categorical features (such as CatBoost) in an innovative gradient boosted decision tree (GBDT) approach. While the CatBoost strategy processes categorization features, the traditional approach does so during the training phase. It can also handle categorization features successfully. As a result, the CatBoost algorithm outperforms the conventional GBDT approach. The CatBoost method, in particular, dynamically organizes and mixes the data sets of each instance. before calculating the average labelled value of the samples, that is the same as the substitute category rate previous to the specified category rate. Make D the training set by entering D= (Z, X). If a permutation of the type $\varphi = [\sigma_1, \dots, \sigma_m]_m^T$ is found, it is substituted by Eq. (12):

$$z_{\sigma_q,l} = \frac{\sum_{p=1}^{q-1}\left[z_{\sigma_p,l} = z_{\sigma_q,l}\right] \cdot X_{\sigma_p} + \alpha Q}{\sum_{p=1}^{q-1}\left[z_{\sigma_p,l} = z_{\sigma_q,l}\right] + \alpha} \tag{12}$$

where q represents the number of sampling groups$(p = 1, 2, \dots, q)$ and $z_{\sigma_q,l}$ is the size of each sample group. The weight of the previous is α, and Q is a prior value. Additional benefit of this strategy is that it uses a novel algorithm to compute the leaf value while choosing the tree structure, hence reducing the issue of overfitting. The CatBoost process can blend all classification characteristics to generate a new category feature. When making a new separation for the tree, the CatBoost approach will recombine it extensively. Another advantage of the CatBoost technique is the use of the forget tree as a predictor. Every leaf index on the tree has a dimension that is equivalent to the binary matrix describing the tree's depth. As a result, the CatBoost approach is widely used. All of the attributes used to produce the prediction technique, including statistical, single-hot encoding, and floating-point numeric characteristics, are binarized

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first. The forecast offset is typically the main hindrance that plagues modeling. In each iteration of GDBT, which uses the same data set each time, the gradient of the algorithm is defined by the function of loss. This gradient estimate variation causes overfitting after training to construct a basic learner. The CatBoost algorithm, which practices ordered boosting instead of the usual method, reduces the gradient estimation bias of conventional procedures. [23].

4.6.2 Overview of ANN

An Artificial Neural Network (ANN) is a computational model inspired by the human brain, playing a fundamental role in the realm of machine learning. ANNs have found successful application in a wide array of tasks, ranging from image and speech recognition to natural language processing and autonomous decision-making. At its core, an ANN is comprised of interconnected artificial neurons, referred to as nodes or perceptrons, which are organized into layers as shown in fig.3. These layers typically include an input layer, one or more hidden layers, and an output layer. The neurons within these layers receive input data, perform computations on that data, and produce corresponding outputs. This network structure is further defined by connections and weights, where neurons in one layer are connected to neurons in adjacent layers through weighted connections that evolve during training to enhance the network's performance. Activation functions introduce non-linearity into the system, crucial for the network to learn intricate patterns and relationships within the data. Common activation functions include the sigmoid, ReLU (Rectified Linear Unit), and hyperbolic tangent functions. Forward propagation carries input data through the layers, while training involves teaching the network to make precise predictions or classifications, employing labeled data and the backpropagation technique to adjust weights based on error or loss. Common loss functions like mean squared error (MSE) or cross-entropy are used for different tasks. The learning rate hyperparameter influences the pace and stability of training. Various hyperparameters, including the number of layers, neurons per layer, and activation functions, require meticulous tuning for optimal performance. Overfitting, a common issue, is mitigated through regularization techniques such as dropout and L1/L2 regularization. After training, the ANN is assessed on separate validation or test data to evaluate its generalization capability, and in practice, it is utilized for inference on new, unseen data. Artificial Neural Networks stand as a versatile and potent tool in modern machine learning, revolutionizing fields like computer vision, natural language processing, and autonomous systems, playing a pivotal role in advancing artificial intelligence [24].

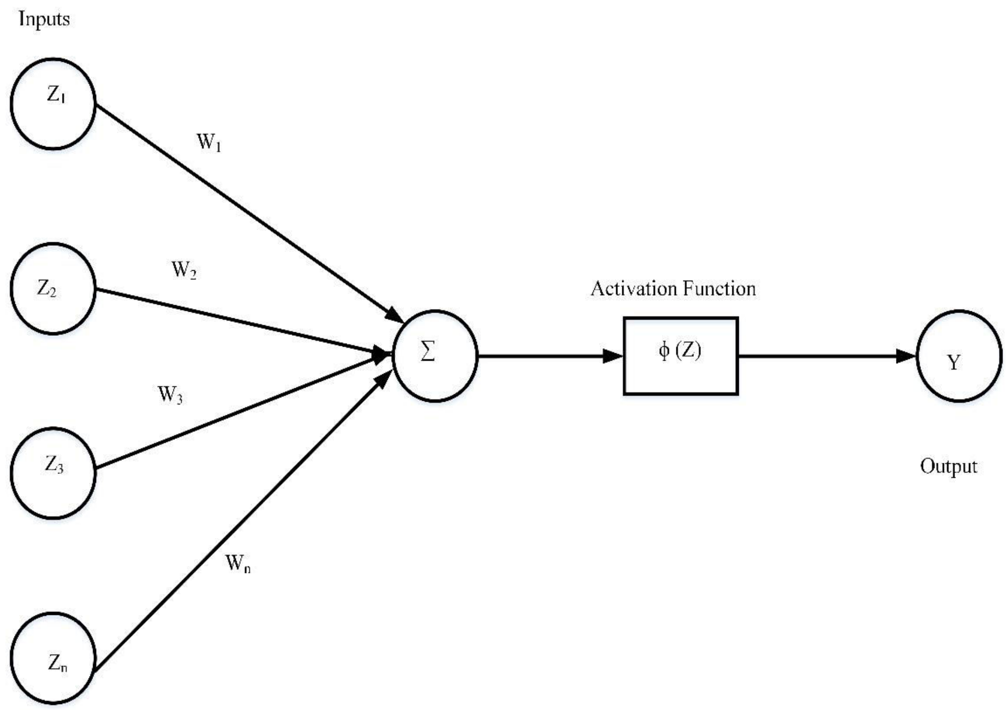

Fig.3. Basic Structure of ANN

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4.6.3 Hybrid CatBoost -ANN for damage classification and Risk Assessment

With the combined feature set in place, the hybrid CatBoost-ANN model is constructed for training. The dataset is divided into training, validation, and testing subsets. The training data is used to teach the model to recognize patterns and relationships in the feature vectors associated with different damage classes. The validation set is used for hyperparameter tuning and model evaluation during training, while the testing set assesses the model's final accuracy and generalization. The hybrid model comprises two main components: the CatBoost component and the ANN component, both connected to a final classification layer. During training, the model learns to classify bridge images based on their damage status. Once the hybrid model is trained, it is ready for inference. New bridge images are processed through both the CatBoost and ANN components to extract features. These features are then fused, and the final classification is made using the classification layer. The model's output provides a classification label indicating the damage status of the bridge image. This label may include information about the type of the damage, especially in scenarios involving multi-class classification.

Table.2. Risk Level of Bridges

Severity Level	Description
Negligible	Very fine or hairline cracks with minimal impact.
Low	Small and shallow transverse cracks with limited impact.
Medium	Moderate transverse cracks requiring attention.
Critical	Deep, extensive, or widespread transverse cracks affecting road quality.

The severity grading table for bridge transverse cracks provides a useful framework for analyzing the state of road surfaces and identifying the best course of action for maintenance and repair. To help road maintenance professionals and engineers, Table 2 defines four separate severity levels, each with its own description. At the Negligible level, you may encounter very fine or hairline cracks that have little impact on the general quality of the road. These cracks are often superficial and have no substantial impact on the structural integrity or safety of the road. While they may not require immediate attention, they should be monitored on a regular basis to ensure they do not deteriorate with time. Moving on to the Low severity level, which consists of modest and shallow transverse cracks with negligible impact. These fissures are still tiny and pose no imminent danger to road users. They do, however, merit some attention because, if left ignored, they have the potential to deteriorate and lead to more serious conditions. To prevent additional deterioration, timely repair or sealing may be required. The Medium severity level is distinguished by moderate transverse cracks that necessitate more extensive care. These fissures are large and deep enough to have an impact on road quality and performance. Maintenance and repair efforts should be prioritized to prevent cracks from spreading or interconnecting, which could lead to more serious structural issues. Finally, deep, large, or widespread transverse cracks have a significant influence on road quality and safety at the Critical severity level. In this case, prompt action is required to repair the cracks and prevent future damage. These flaws may jeopardize the structural integrity of the road, posing risks to motorists. Comprehensive repair and rehabilitation operations are required to return the road to its original state and assure safe navigation. Road maintenance experts can use this severity categorization chart to systematically examine the health of transverse cracks and make informed judgments regarding the necessary level of intervention, thereby ensuring the durability and safety of our road infrastructure.

The model's performance is assessed using various metrics like accuracy, precision, recall, F1-score, and confusion matrices. These metrics help gauge how effectively the model classifies bridge images and its ability to generalize to unseen data.The hybrid CatBoost-ANN model for damage classification in bridge images combines the feature engineering capabilities of CatBoost with the image processing strengths of ANNs to create a robust and accurate classification system. This integration of complementary techniques enhances the model's accuracy and reliability, contributing to the safety and maintenance of critical infrastructure by enabling efficient detection and classification of damage in bridge structures. The research workflow begins with the introduction of the RDD2022 dataset, high-resolution bridge images categorized into four damage types. The dataset undergoes a meticulous pre-processing pipeline involving the application of an anisotropic diffusion filter (ADF) to reduce noise and enhance image quality, followed by a Hann mean filter (ADHF) to further refine the images. Subsequently, Otsu thresholding is used for image segmentation, effectively isolating damaged areas. Feature extraction is performed using the Grey Level Cooccurrence Matrix (GLCM) technique, capturing textural characteristics. To optimize feature selection, the Cuckoo Search

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Algorithm is applied. Finally, a hybrid classification model combining CatBoost and Artificial Neural Networks (ANN) is developed, trained on training, validation, and testing subsets, enabling it to classify bridge images based on damage status. The model's output provides precise damage classification labels, and its performance is rigorously evaluated using various metrics, resulting in the creation of an accurate and reliable hybrid CatBoost-ANN model for bridge damage classification, ultimately contributing to infrastructure maintenance and safety. The flowchart is depicted in fig.4.

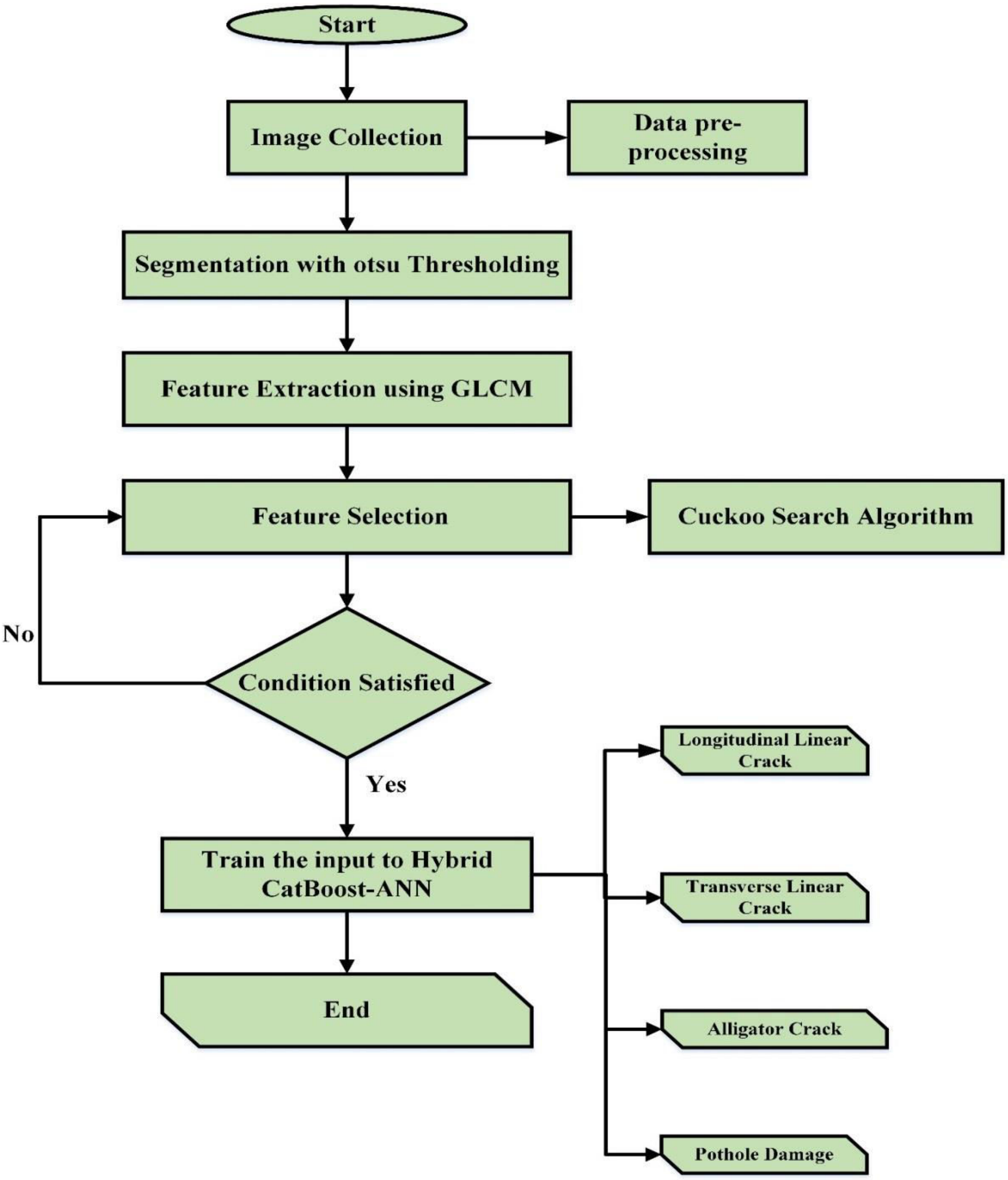

Fig.4.Flowchart of Hybrid CatBoost -ANN method

V. RESULT AND DISCUSSION

The results and discussion of this study demonstrate the effectiveness of the proposed methodology in bridge damage classification. The hybrid CatBoost-ANN model achieved impressive classification accuracy and robustness when applied to the RDD2022 dataset. The rigorous evaluation using metrics such as accuracy, precision, recall, F1-score, and confusion matrices confirmed the model's ability to accurately classify bridge images based on damage types. The

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optimized feature selection through the Cuckoo Search Algorithm contributed to reducing computational complexity and overfitting issues. Furthermore, the incorporation of data from multiple countries in the RDD2022 dataset enhanced the model's generalizability, making it applicable in diverse geographical contexts. The developed hybrid model serves as a valuable tool for structural health monitoring and risk assessment of bridges, enabling efficient and timely identification of damage for necessary maintenance and repair efforts. Overall, this research underscores the importance of advanced image processing techniques and machine learning algorithms in enhancing infrastructure safety and maintenance practices, ultimately ensuring the longevity and reliability of critical bridge structures.Fig.5 illustrates training and testing Images.

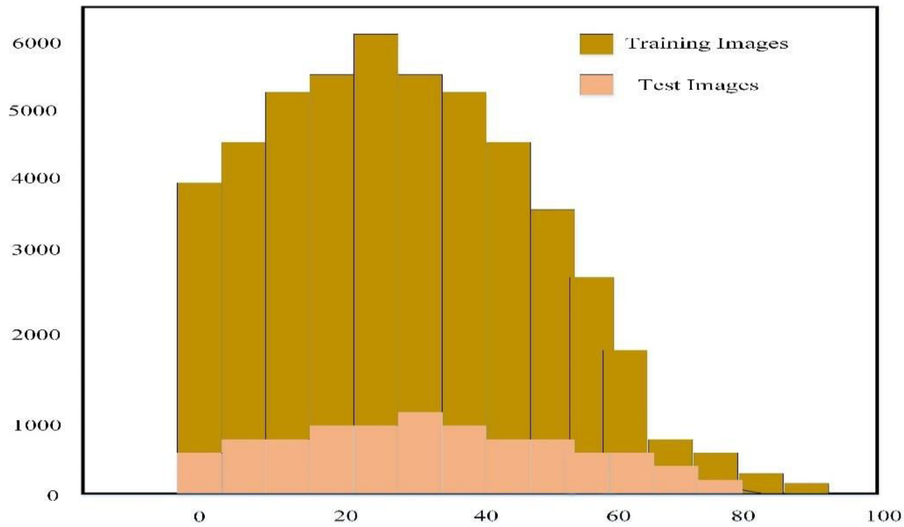

Fig.5.Training and Test Images.

Table 3 showcases the training and validation accuracy values across different iterations for a hybrid CatBoost-ANN model. At the initial iteration (iteration 0), both training and validation accuracies stand at 0, indicating a model yet to be trained. As training progresses, the training accuracy significantly improves, reaching 99% at iteration 90. The validation accuracy follows a similar upward trend, rising from 0% initially to 99% at iteration 90. Notably, the model exhibits rapid learning, particularly in the early iterations, and achieves high accuracy on both the training and validation datasets, suggesting effective generalization and strong performance. This table provides insights into the model's training progress and its ability to accurately classify data, highlighting its strong convergence and generalization capabilities in a hybrid CatBoost-ANN framework.

Table 3. Training and Validation Accuracy of proposed Hybrid CatBoost-ANN

Iteration	Training Accuracy	Validation Accuracy
0	0	0
10	95	85
15	95	93
20	88	95
25	80	96
50	95	98
75	95	98.5
90	99	99

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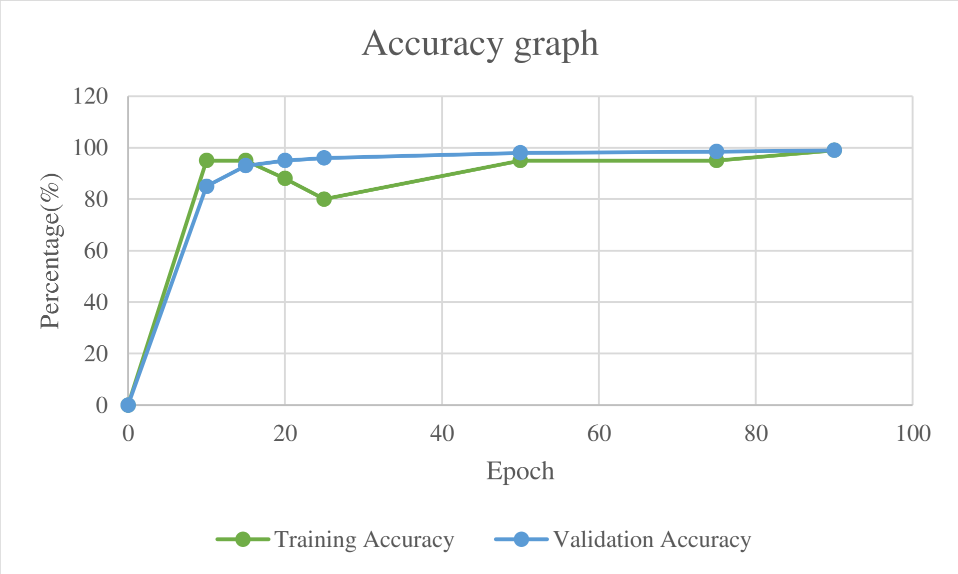

Fig.6.Accuracy of Hybrid CatBoost-ANN

Table 4 illustrates the training and validation loss values at different iterations for a hybrid CatBoost-ANN model. Initially, at iteration 5, the training loss is relatively high at 3.5, which gradually decreases as the model learns, reaching 0.1 by iteration 60. In contrast, the validation loss starts at 0.5 and remains relatively steady throughout the initial iterations but eventually decreases to 0.1, mirroring the training loss's trend. This pattern suggests that the hybrid CatBoost-ANN model rapidly converges and exhibits effective generalization to unseen data, as evidenced by the consistently low validation loss values. This table provides insights into the model's learning process and its ability to minimize loss, indicating the model's overall performance and convergence behavior during training.

Table 4. Training and Validation Loss of proposed Hybrid CatBoost-ANN

Iteration	Training Loss	Validation Loss
5	3.5	0.5
10	0.5	0.5
15	0.9	0.5
20	1.7	0.6
25	0.6	0.6
30	0.2	0.3
40	0.1	0.2
60	0.1	0.1

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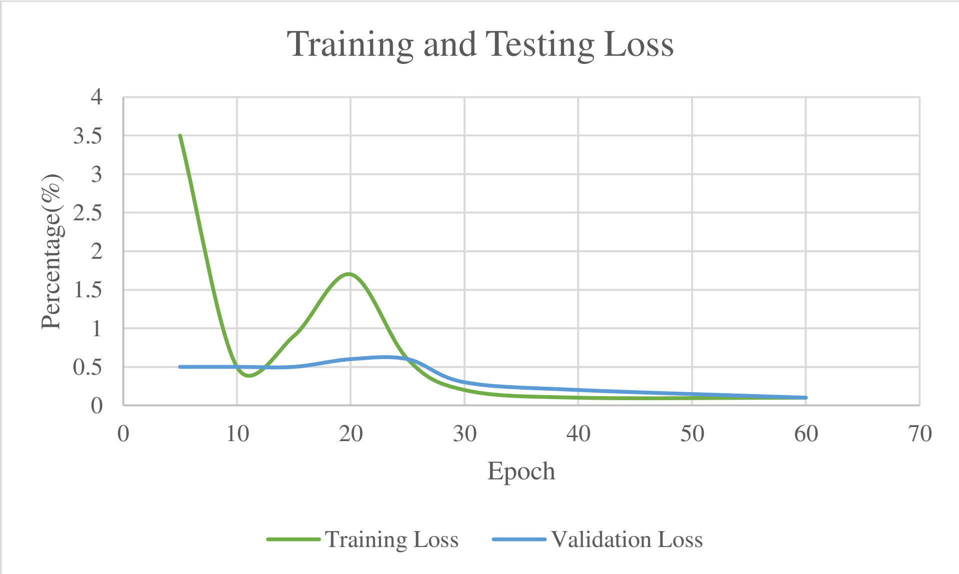

Fig.7. Loss of Hybrid CatBoost-ANN

The proposed innovative Hybrid CatBoost-ANN for Recognising and Classifying Bridge Damage is explained in this part along with the experimental findings. Using criteria like precision, accuracy, f-measure, recall and error rate, the suggested hybrid CatBoost-ANN strategy is assessed and contrasted with the conventional methods. The following is an explanation of the operational metrics taken into account in the designed Cuckoo Search Optimisation.

Accuracy: In all instances under investigation, it determines the percentage of genuine outcomes, including true positives and true negatives. It is stated in Equation (13),

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

Precision: Precision is the ratio of precisely expected positive outcomes to all projected positive events. Equation (14) is used to compute the precision.

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

Recall: The recall counts the number of samples that were actually positive but were mistakenly projected to be positive. Using equation (15), get the recall value.

$$Recall = \frac{TP}{TP+FN} \tag{15}$$

where FP represents false positive pixels, FN symbolizes false negative pixels, TP signifies true positive pixels, and TN describes true negative pixels.

F1-score: Recall and accuracy are related in the classification job. Although a high score for both is ideal, excellent accuracy with low recall or high recall with low accuracy is more often the case. The F1-score definition is shown in equation (16).

$$F1 - score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{16}$$

Area Under the Curve (AUC) has been calculated to estimate hybrid CatBoost-ELM overall performance using Eq.19.

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$$AUC = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \quad (19)$$

where FP represents false positive pixels, FN symbolizes false negative pixels, TP designates true positive pixels, and TN describes true negative pixels. Fig.8 illustrates ROC curve of Hybrid CatBoost-ANN.

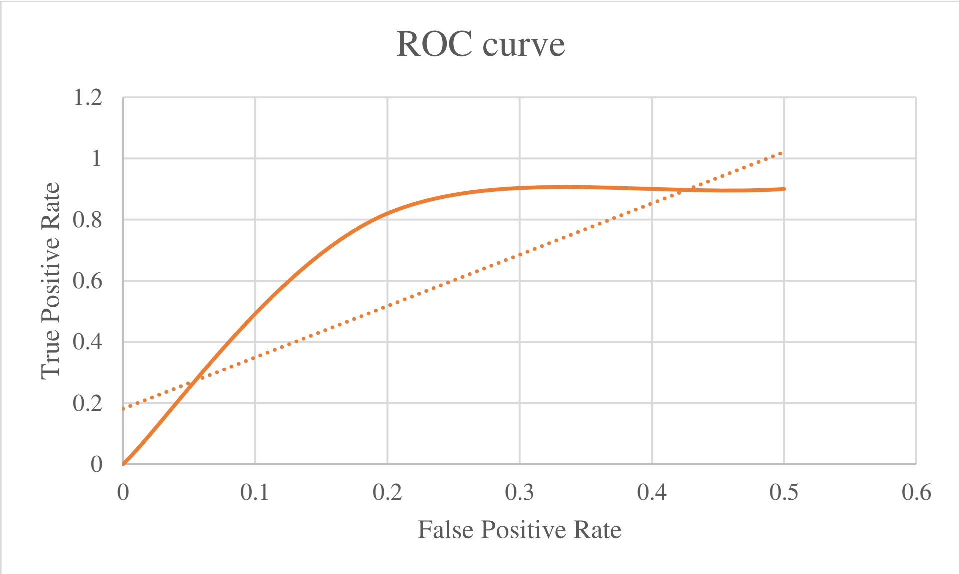

Fig.8.ROC curve for proposed Hybrid CatBoost-ANN.

Table 5 compare the performance metrics of three different methods for a classification task. The first method, Customized CNN, achieves an impressive precision score of 0.997, indicating its ability to correctly classify a high proportion of positive cases, although it exhibits a somewhat lower recall of 0.85, suggesting that it may miss some true positive instances. The resulting F1-Score for Customized CNN stands at 0.918, striking a balance between precision and recall. In contrast, the Feature Fusion approach demonstrates a lower precision of 0.873 but compensates with a slightly higher recall of 0.885, resulting in an F1-Score of 0.879. Lastly, the Proposed CatBoost-ANN method outperforms both in terms of precision with a score of 0.998 and recall with 0.91, leading to an F1-Score of 0.924, indicating its superior overall performance in this classification task. These results highlight the trade-offs between precision and recall, with the CatBoost-ANN method emerging as the most promising choice for this specific task due to its high precision and substantial recall. Fig.9. shows Performance Metrics of Proposed Hybrid CatBoost-ANN.

Table 5. Comparison of Performance Metrics with Existing Methods

Methods	Precision	Recall	F1-Score
Customized CNN[25]	0.997	0.85	0.918
Feature Fusion[26]	0.873	0.885	0.879
Proposed CatBoost-ANN	0.998	0.91	0.924

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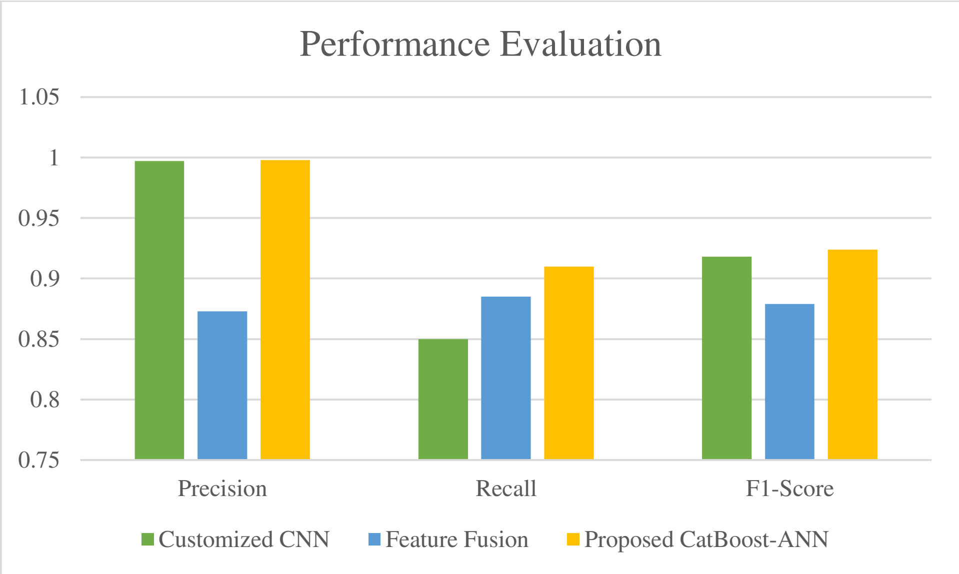

Fig.9.Performance Evaluation of Hybrid CatBoost-ANN

VI. CONCLUSION

In conclusion, study presents a novel Hybrid CatBoost-ANN approach for Recognizing and Classifying Bridge Damage, demonstrating its exceptional performance through a comprehensive evaluation of key performance metrics. The proposed model showcases rapid learning and convergence, as evidenced by its remarkable progression in both training and validation accuracy, reaching 99% accuracy. Moreover, the model consistently achieves low training and validation loss values, highlighting its effective generalization. Comparing proposed method to existing approaches, Customized CNN and Feature Fusion, the Proposed CatBoost-ANN excels with a precision score of 0.998 and recall of 0.91, resulting in an impressive F1-Score of 0.924. These findings emphasize the Hybrid CatBoost-ANN's superior ability to balance precision and recall, making it the most promising choice for the task of bridge damage classification. Overall, study demonstrates the potential of this innovative hybrid model in the domain of structural damage assessment, offering both accuracy and robust generalization.

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