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UTILIZING DATA MINING TECHNOLOGY FOR STRUCTURAL ANALYSIS IN CIVIL ENGINEERING SYSTEMS

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Abstract

In civil engineering, structural analysis typically involves evaluating the integrity and safety of infrastructure such as bridges, buildings, and dams. Data mining helps automate this process by analyzing vast amounts of data to detect signs of deterioration, structural defects, or failure risks. This study explores an application of data mining technology for a detection and analysis of structural defects, such as cracks and delamination, in civil engineering infrastructure, specifically bridges, using deep learning-based semantic segmentation. A dataset comprising 1,250 images sourced by an Internet, on-site inspections, and GoogleStreetView was utilized. The data underwent preprocessing steps including resizing, data augmentation (rotation, reflection, translation, and scaling), and pixel-wise annotation to classify pixels as "Crack," "Delamination," or "Background." The methodology leverages the DeepLabV3+ architecture with pretrained ResNet-18 and ResNet-50 as encoders, incorporating ATROUS Spatial Pyramid Pooling (ASPP) tocapture multi-scale contextual information while maintaining spatial resolution. Data mining techniques were employed to optimize model hyperparameters and enhance an accuracy of defect detection. The outcomes shows that a ResNet-50 model outperformed others, achieving a validation accuracy of 91.04%, with superior performance in detecting "Delamination" and "Background" classes. The method performed well in a range of illumination and environmental circumstances, despite the fact that identifying "Crack" flaws was more difficult. This study demonstrates the potential of DL and data mining approaches for accurate, automated structural analysis in civil engineering systems, providing a practical means of infrastructure maintenance and monitoring.

***Keywords:** Data Mining (DM), Structural Analysis, Civil Engineering, deep learning, semantic segmentation, ATROUS.*

I. INTRODUCTION

The architecture, engineering, and construction (AEC) industry uses a lot of resources, thus in recent decades, there has been a growing concern about sustainability and efficiency in this sector

[1]. Designing, constructing, operating, and maintaining buildings and infrastructures, including a wide range of works including highways, bridges, and residences, is the purview of civil engineers [2]. While accounting for a sizable portion of the economy, the AEC sector has a reputation for requiring a lot of workers, being inefficient, and having a negative effect on the environment [3] [4]. Rehabilitating and upgrading infrastructure to make it safer and last longer is the main focus of civil engineers in areas like the UK, France, and Italy that are dealing with the effects of an ageing infrastructure [5]. Infrastructure that reduces environmental impact while maximising efficiency and longevity is being more and more of a responsibility of civil engineers as the global community comes to terms with the pressing need to optimise resource utilisation and address environmental issues [6][7].

Problems with age, material degradation, unexpectedly high loads during design, improper use, environmental interventions, and natural disasters are among the many challenges that civil constructions face today. Tragically, they could sustain damage that jeopardises the structural integrity and safety of the building [8]. The efficient functioning of structural systems and user safety are two of the main priorities of civil engineers throughout the building life cycle [9]. To prevent structural problems brought on by ageing, abuse, climate change, or wear and tear, it is crucial to continuously check the condition of the structure, especially in order to identify abnormalities early [10]. When dealing with delicate structures like large buildings, bridges, viaducts, and geotechnical projects, this becomes extremely important [11]. Structural health monitoring (SHM) has become an effective tool for detecting structural analysis issues early on, as visible human checks are prone to inaccuracies [12]. The most important aspect of structural analysis is seen to be damage detection, one of the stages of damage identification established by [13]. The following steps are included in this process, which is defined as the automated and systematic detection of damage: localisation and severity evaluation. The localisation and quantification of damage require precise identification of its occurrence, which is assisted by new papers on damage detection.

Data Mining (DM) refers to the process of discovering value in statistics by gleaning information that was previously unknown. There are a lot of technical specialisations that have already conducted data mining investigations. DM has replaced the dollar. It is a state-of-the-art technique for performing parameter analyses on recordings and then distilling the results into useful information [14]. Users may examine records based on a plethora of factors, and the system sorts them according to the identified correlations. From a technical standpoint, DM is the process of discovering patterns or correlations among multi-fields in large relational databases [5]. Data mining is undeniably useful for extracting useful information from datasets. It is the process of transforming large datasets into the necessary forms. It is the method by which various patterns in massive datasets are unearthed. The evaluation of the current databases produces new data. Data mining tools and methods are shown in this study, along with their importance and applications in several sectors of civil engineering. There are methodologies that involve analysing photographs of visible surfaces of structures with computer vision utilizing data mining-based DL techniques that is broad part of the data analytical field in civil engineering, the best example of DL models is CNNs. This types of classical modal data analysis is widely employed among several approaches for detecting structural damage in civil engineering [15][16].

A. Motivation and Contribution of the Study

The need for better and more dependable ways to track and maintain the stability of civil engineering structures, especially bridges, is what drives this effort. Time, human error, and delays are the downfalls of manual inspection procedures, which put safety at risk. By utilizing data mining and deep learning technology, this study aims to automate the detection of structural defects like cracks and delamination using semantic segmentation. The approach offers a scalable, cost-effective solution for detailed, pixel-level analysis of infrastructure, addressing challenges such as varying environmental conditions and improving the efficiency of long-term maintenance and safety monitoring. Here are key contributions of the study:

- This study introduces an automated system for identifying and analyzing structural defects such as cracks and delamination in bridge infrastructure, leveraging deep learning-based semantic segmentation.
- The study used a broad dataset consisting of 1,250 photos obtained from various sources, including the Internet, on-site inspections, and Google Street View. This ensures that the algorithm can withstand certain real-world scenarios.
- The research guarantees that the model may generalise successfully to different structural situations and environmental variables by utilising data augmentation methods such as rotation, reflection, translation, and scaling.
- The study employs pixel-wise annotation for classifying defects as “Crack,” “Delamination,” or “Background,” ensuring precise defect detection at the pixel level, which is crucial for infrastructure inspection.
- To improve detection accuracy while keeping spatial resolution intact, the work employs DeepLabV3+ with pretrained ResNet-18 and ResNet-50 as encoders, using ASPP to get multi-scale contextual information.
- The study optimizes key model hyperparameters, including learning rate, mini-batch size, and momentum, improving training efficiency and ensuring optimal performance in detecting structural defects, thereby supporting proactive maintenance and long-term sustainability of infrastructure systems.

B. Structure of paper

The paper is split into many important sections. Section II discussed the literature review analyses current methodologies. The methodology outlines data collection, annotation, preprocessing, and the semantic segmentation technique utilizing DeepLabv3+ with ASPP provide in Section III. Section IV evaluates performance measures, and the findings and discussion outline them. Section V delves into the conclusion and discusses potential future research.

II. LITERATURE REVIEW

This section examines the current literature on data mining technologies for structural analysis in civil engineering, concluding with a summary of the literature review in Table 1.

S.A. Timashev et al. (2015), article details the authors' creation of a brand-new, cutting-edge, multidisciplinary Master’s Program at the Civil Engineering Institute of the Ural Federal University called the "Safety of Civil Engineering Critical Infrastructures and Territories" that will run for two years. The third year of the program's effective execution has passed. Provided in both Russian and English, it is predicated on the latest paradigm of resilient critical infrastructure and, by extension, on this idea, on the resilience and safety of the area[17].

Angel Ramos et al. (2015), This work introduces a chipless RFID sensor with ultra-wideband time-coding for use in civil engineering material quality detection. Backscattering is the foundation of the sensor. To measure permittivity, one uses a change in latency, and to measure permittivity and material loss, one uses a change in amplitude. To back up the idea, we provide both measured and simulated data[18].

Oai Ha et al. (2016), data gathered from 95 active civil engineers in the Pacific Northwest was factor analysed in this research. It was shown in the research that engineers' answers to the SCI may show how well they understand engineering practice in terms of cohesive concepts. Experts' traits in processing, organising, and storing information in chunks may be shown by the engineers' ability to combine discrete ideas into wider and meaningful ones in this research[19].

Hong-xia Cai et al. (2017), Civil aircraft quality data is characterised by disorder association, complex structure, and large amounts of data. To address this, we present the Apriori algorithm for data mining association analysis and the Splunk platform for big data. By combining their strengths, we can effectively reduce the complexity of quality data analysis and bring the data into a coherent state. The findings demonstrate the effectiveness and high efficiency value of the devised approach[20].

A. Antunes et al. (2018), analyses information produced by sensors embedded in massive civil engineering projects and the challenge of identifying outliers. The method can detect and eliminate the majority of outliers in the demonstration and evaluation datasets by utilising Manual Acquisition System measurements in conjunction with a clustering algorithm (DBSCAN) and baseline methods (Multiple Linear Regression and standard deviation thresholds). This automated technique enhances data quality, which in turn influences structural safety decision-making [21].

Liqiang Xie et al. (2018), A new integrated surface acoustic wave (SAW) pressure sensor is proposed in this research for the purpose of monitoring civil engineering constructions. The SAW device's strain behaviour and pressure measurement are thoroughly examined in order to optimise the construction. On the SAW substrate, the reflectors and inter-digital transducers are positioned with purpose. Using a lift-off method, the SAW device is manufactured. The sensor is defined by an analyser of networks. Both the nonlinearity and the pressure sensitivity were measured at 1.02%. Between 0 and 500 kPa, the highest absolute inaccuracy is 2.9°[22].

M. Kaya et al. (2018), The variables impacting the concrete's compressive strength after 28 days were the subject of a data mining investigation that made use of the Concrete Slump Test Data Set available in the UCI Machine Learning Repository. A feature selection approach that is used is the Artificial Bee Colony Algorithm. The research found that the Random Forest Algorithm, which used just three features—cement, fly ash, and water—had the best success rate, with an accuracy of 91.2621%. This indicates that by employing fewer concrete components, it is feasible to forecast the

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compressive strength of concrete with a ratio exceeding 90%[23].

This table1 summarizes the key literature on utilizing data mining in civil engineering, with an emphasis on structural analysis and material quality monitoring. Each entry includes the methodology, findings, and the specific contribution to advancing data mining techniques in civil engineering.

Table I. Summary of the Related Work on Structural Analysis in Civil Engineering Systems Using Various Tools And Techniques

Author(s) & Year	Objective/Focus	Methodology/Approach	Key Findings/Results	Contribution to Data Mining in Civil Engineering
S.A. Timashev et al. (2015)	Development of a new interdisciplinary Master's Program focusing on critical infrastructure safety.	Program development and interdisciplinary curriculum design	The program is successful in enhancing the resilience of civil engineering systems and regions.	Focus on resilience in infrastructure using an interdisciplinary educational approach.
Angel Ramos et al. (2015)	Developing an RFID sensor to detect the quality of materials in civil engineering.	Backscattering-based RFID sensor, delay/amplitude change to detect permittivity	The RFID sensor successfully detects the permittivity and loss of materials with high accuracy.	Pioneering the use of RFID technology and data mining for material quality analysis.
Oai Ha et al. (2016)	Analyzing responses to SCI data to understand engineers' conceptual knowledge in civil engineering.	Factor analysis of SCI data from practicing engineers	Reveals the conceptual coherence and knowledge chunking of engineers for better knowledge organization.	Utilizes data mining techniques to analyze professional knowledge and expertise.
Hong-xia Cai et al. (2017)	Using data mining algorithms to analyze large sets of quality data from civil aircraft.	Apriori algorithm and Splunk platform for data association analysis	The method successfully reduces data complexity and improves analysis efficiency for civil aircraft quality data.	Introduces data mining techniques to handle complex quality data in engineering.
A. Antunes et al. (2018)	Detecting and removing outliers in datasets generated by sensors in civil engineering structures.	DBSCAN clustering, Multiple Linear Regression, standard deviation-based thresholds	The method effectively detects and removes outliers, improving data quality and supporting structural safety decisions.	Improves data quality in structural monitoring using data mining and clustering.
Liqiang Xie et al. (2018)	Designing a SAW pressure sensor for monitoring pressure in civil engineering structures.	SAW device analysis, strain behavior, and pressure measurement	The sensor provides accurate pressure sensitivity and low error margins for structural monitoring.	Advances sensor technology with data mining for real-time structural monitoring.

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M. Kaya et al. (2018)	Analyzing factors affecting the compressive strength of concrete using data mining.	Artificial Bee Colony Algorithm for feature selection, Random Forest for prediction	Random Forest predicts concrete compressive strength with over 90% accuracy using just 3 features.	Demonstrates the power of machine learning in predicting material properties.

III. METHODOLOGY

The methodology employs leverages data mining technology to identify and analyze structural defects such as cracks and delamination in bridge infrastructure using semantic segmentation based deep learning techniques. A dataset consisting of 1,250 images was prepared for analysis by resizing them to 300×300 pixels, augmenting them with rotation, reflection, translation, and scaling, and then annotating each pixel using MATLAB's Image Labeller. Pixels were classified as either "Crack," "Delamination," or "Background." This preparation ensures robust training data capable of generalizing across diverse conditions. The model uses DeepLabV3+ with pretrained ResNet-18 and ResNet-50 as encoders, using ASPP to preserve spatial resolution while capturing multi-scale contextual information. Deep learning with ImageNet weights enhances performance and reduces training time. Optimized hyperparameters and the Stochastic Gradient Descent algorithm with momentum minimize Cross-Entropy Loss for precise pixel-level segmentation. The dataset was split 80/20 for training and validation, achieving improved mean accuracy and Intersection over Union (IoU), demonstrating robustness across varying lighting, textures, and backgrounds. This methodology ensures accurate detection and classification of structural defects under civil engineering conditions, providing a scalable solution for infrastructure monitoring. This study's methodological flowchart is shown in figure 1.

A. Data collection

Online resources, in-person bridge inspections, and mapping services like Google Street View comprise the 1250-image collection. Several forms of noise impact the photos, which depict real-life environmental circumstances with several backdrops. This ensured a dataset with varied image quality, resolutions, and backgrounds, making the model robust to real-world conditions.

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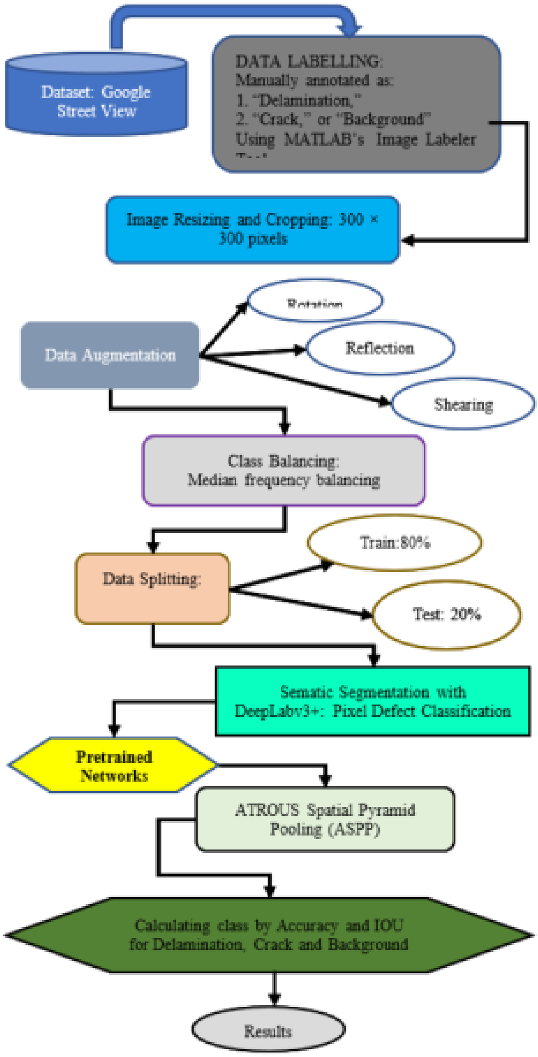

Fig. 1. Flowchart of the methodology

The below steps of methodology that shows in figure 1:

B. Data labelling

A hand annotation was performed on the images by utilizing the Image Labeler in MATLAB. The labels "Delamination," "Crack," and "Background" were assigned to each and every pixel. Which is beneficial in When it comes to training semantic segmentation models, accurate labelling is absolutely necessary. This is because it guarantees that every pixel in the pictures belongs to the appropriate category.

C. Image resizing

In order to maintain a consistent resolution of 300 × 300 pixels, every image underwent a process of resizing and cropping. The utilization of standardized picture dimensions contributes to the optimization of computing resources and the enhancement of training efficiency.

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D. Data Augmentation

Augmentation enhanced the quantity of the dataset by producing a variety of different copies of the photos that were already there. This helped to reduce instances of overfitting and improved the model's capacity to generalize.

1. Image Augmentation

Randomized augmentations like rotation, reflection, and shear ensure the dataset is invariant to image distortions and environmental variations.

- **Rotations:** Images were twisted at random angles to represent various flaw orientations.
- **Translations:** Shifting images horizontally or vertically to mimic positional variations.
- **Scaling:** Adjusting image sizes to represent defects at various distances.

2. Manual Labeling (Pixel Wise Predictions):

Deep networks are able to provide pixel-by-pixel forecasts and depth map predictions from a single image [24] [25]. The most effective approaches used to separately identify pixels using hand-engineered characteristics before deep networks came along. Pixel-wise segmentation ensures high precision in ground truth data, essential for supervised learning tasks like semantic segmentation.

E. Class Balancing

It ensures the model performed well for all classes despite their frequency in the dataset. The Median frequency balancing was applied to assign higher weights to underrepresented classes, such as cracks.

1. Median Frequency Balancing

Median frequency balancing is a technique used to address class imbalance in datasets. It assigns weights to each class based on the median frequency of pixels belonging to that class compared to the frequency of pixels in all classes. This ensures that underrepresented classes have a more significant contribution during the training process calculate equ.1.

$$Wc = \frac{median\ f}{fc} \dots \dots (1)$$

Where, f is the frequency of pixels for all classes and fc is the frequency of pixels for class c. This method ensures that classes with fewer pixels (e.g., "Crack") are assigned higher weights, making their contribution more significant during training. The frequencies for each class were computed, and the median frequency was used to calculate weights:

- **"Crack":** Fewest pixels, so it was assigned the highest weight.
- "**Delamination":** Moderate frequency, assigned a medium weight.
- **"Background":** Dominant in most images, assigned the lowest weight.

2. Pixel Frequency Calculation:

First pixel frequency calculation is done for each class. The pixel frequency, which is the fraction of all pixels in all photos that belong to a certain class split by the total numberof pixels in some photographs. This determines how frequently each class occurs in the dataset, as equ.2.

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$$fc = \frac{Number\ of\ pixels\ in\ class\ c}{total\ images\ contaning\ class\ c} \ldots .. (2)$$

Now, compute the median of all class frequencies across the dataset. This serves as a reference frequency.

F. Data Splitting

The expanded dataset was divided into 80% for training (2000 photos) and 20% for validation (500 images). The rationale is to maintain a balance between model training and the assessment of its generalization performance.

G. Data Mining Technique

Data mining is the practice of discovering valuable insights and patterns in large datasets [26]. Knowledge discovery process, data mining, knowledge extraction, data/pattern analysis, and similar terms all describe the same thing.

1. Semantic segmentation

It involves giving each pixel in the picture a meaningful label. Semantic segmentation differs from standard segmentation in that it assigns a single label to many objects belonging to the same class. The areas should be significantly connected to the objects or characteristics of interest in the picture to support their importance for image analysis and assessment [27]. The ability to segment pictures meaningfully paves the way for more sophisticated image processing operations, such as the generation of detailed feature, object, layout, and scene descriptions, as opposed to the more rudimentary transformations of greyscale or colour images into several other images[28]. There are two further ways to categorise segmentation methods: contextual and non-contextual. The spatial interactions between an image's components are heavily used by contextual approaches.

This study utilizes DL-based semantic segmentation to examine flaws in civil infrastructure, representing a form of data mining utilized in structural analysis. It takes and analyses data from photos to detect and measure faults such as cracks and delamination. The model selection process utilizing CNN for semantic image segmentation to classify each pixel, alongside the depiction of the DeeplabV3+ architecture with ASPP for structural analysis in civil engineering systems.

a) CNN

Semantic picture segmentation uses a convolutional neural network (CNN) to classify each pixel. Deep layers often store high-level information, whereas shallow layers store low-level characteristics in a CNN. Pooling or stride convolutions down-sample feature maps to reduce deep neural network computational overhead in image classification applications. Encoder/decoder is needed for full-resolution semantic predictions in image segmentation. The encoder part uses low-resolution feature maps as input and learns class differentiation, while the decoder part uses full-resolution segmentation maps as output. The down-sampling component is a complex CNN containing convolutional, pooling, and activation layers, structures of the Semantic segmentation convolution neural network show shown in Figurehe encoder component is significantly reduced by repeated pooling methods, resulting in irretrievable decoder information loss [29] Introduced

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the DeepLabv3+ decoder to enhance segmentation outcomes. The proposed approach preserves spatial resolution while acquiring multi-scale contextual information via ASPP. The last step in determining the class of each pixel is the soft-max layer, which uses a series of transpose convolutions to improve the feature maps' resolution.

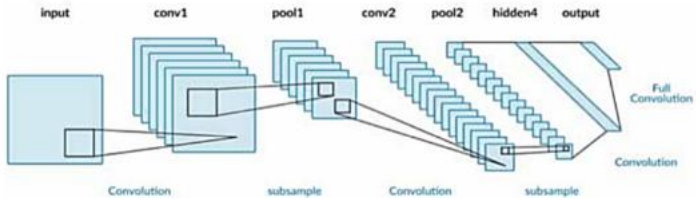

Fig. 2. Semantic segmentation convolution neural network

b) Convolutional layer

Each layer uses filters to automatically extract visual characteristics. Nodes of each layer send extracted features to subsequent levels to improve 105 features. The original image's local dependencies depend on weights automatically changed during training. The activation function at the end of the Convolutional layer allows for nonlinear changes, as convolution is inherently linear. The Re-LU is the activation function of choice for the majority of cases. It immediately outputs the input value or zero in the case of negative inputs. Re-LU speeds up neural network backpropagation training due to its linearity for positive values. One-dimensional convolution produces equ.3:

$$\mathbf{y(i)} = \sum_{k=1}^{k} \boldsymbol{x(i+k).w(k)+b} \dots\dots (3)$$

If x (i) represents an input, w(k) denotes a filter of length K, and b signifies a bias. The systematic application of the filter across an image facilitates the extraction of features from any location within the image, resulting in the creation of a feature map. A convolutional layer takes an image x with dimensions m × n as its input. The input picture has more dimensions than the convolutional layer, which has k filters (kernels) with sizes p × q [30]. Stiding over one pixel produces a collection of k feature maps with dimensions (m − p + 1) × (n − q + 1), which is the output of the convolutional layer.

c) Pooling layer

It is common practice to use a pooling layer after a convolutional layer. A set of convolutional layer pixels are linked to a single pooling layer map pixel. By repeatedly sampling the pooled pixels, the pooling layer's pixel size is increased to match that of the convolutional layer, allowing for more efficient sensitivity computing. Two typical approaches to pooling, Max Pooling and Average Pooling, are used to extract the important characteristics. Whereas Average Pooling calculates the mean value, Max Pooling delivers the largest value for a section of the feature map covered by the kernel[31].

2. DeeplabV3+ architecture with ASPP

The architecture of the Deeplabv3+ is shown in Fig. 5. Deeplabv3+ contains three modules: Encoder, Decoder and ASPP module. A feature map's output stride, defined as the ratio of the input image's spatial resolution to the final output resolution, is 16, and the Encoder module

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progressively decreases the feature maps while capturing texture information from 100x100 pictures. These more complex encoded characteristics are sent into the four dilated convolutions of the ASPP module, each of which has a unique dilated rate. Expanding the model's range of vision allows it to learn features at various sizes[32]. These generated features extract the different scales of information and integrate with convolutional layers, as shown in Figure 3. The spatial pyramid pooling layers are capable of receiving input features of different sizes and outputs a feature map of fixed size. In the decoding part, the resolution of feature maps is restored by the decoder module to recover the input images.

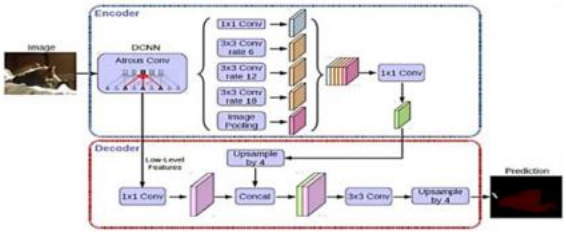

Fig. 3. DeeplabV3+ Architecture

3. Pretrained model

The pretrained models are employed to enhance the accuracy of the models presented here. The ResNet-18 and ResNet-50 models are employed in this research; a detailed explanation of the models is provided in the subsequent part.

a) Res-Net-18

Res-Net was developed by Kaiming He [33] in 2016. Deeper networks, which are notoriously difficult to train, were taught using a residual learning style. Refining the network layers allowed them to learn residual functions by referencing the layer inputs. Based on the findings, deeper networks that use residual learning are able to optimize well and attain good accuracy[34].

The Res-Net-18 model takes its architectural cues from the schematics and PY-Torch library. The training accuracy problems that emerged as deep neural networks became deeper are handled by the Res-Net architecture, which stands for residual neural network. Res-Nets has been a reliable approach for training big CNNs ever since. Figure 4 depicts the original Res-Net-18 architecture.

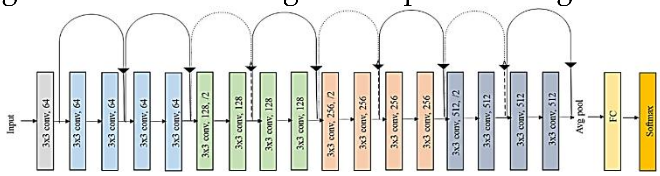

Fig. 4. Original ResNet-18 Architecture

b) Res-Net-50

This 50-layer CNN is called ResNet-50. The training performance is improved, loss is reduced, and knowledge gain is preserved thanks to Res-Net's residual connections between layers [33]. ResNet-50 outperforms conventional classification networks in terms of both performance and computing cost. Figure 5 represents the Res-Net50 model architecture.

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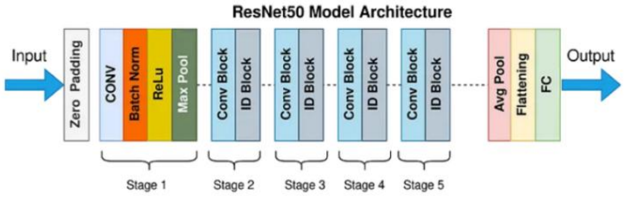

Fig. 5. Res-Net50 model architecture

4. ATROUS Spatial Pyramid Pooling (ASPP)

Deep learning-based semantic segmentation is used for preprocessing and analysis. Multi-scale feature extraction encoder-decoder structure using ASPP. ATROUS convolution is essential for managing DCNN feature resolution and filter field-of-view for multi-scale data. Also known as "dilated convolution". ATROUS rate r sets kernel gaps. Normal convolution uses ATROUS convolution with r = 1. ATROUS convolution expands vision with the same parameters and computational complexity, improving information capture. Figure 6 shows how dilation rates improve field of view. Example picture from our dataset is in Figure 6(a). Figure 6(b) displays that dilation rate 1 uses the surrounding 9 pixels like traditional convolution. Collected edge data is erroneous. Dilation increases the range of view and reveals water and background pixels[35].

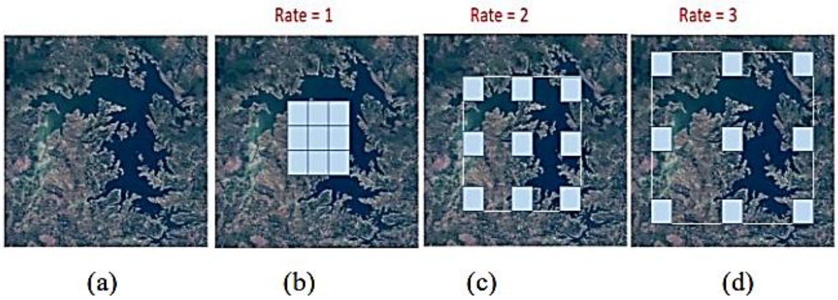

Fig. 6. Example of RGB image with different dilated convolution layers (a) Sample RGB image (b-d) sample RGB image with Rate = 1, 2 and 3.

In ASPP module, with the help of ATROUS convolution by increasing the field of view using the different dilated rates, it extracts the different scales of information.

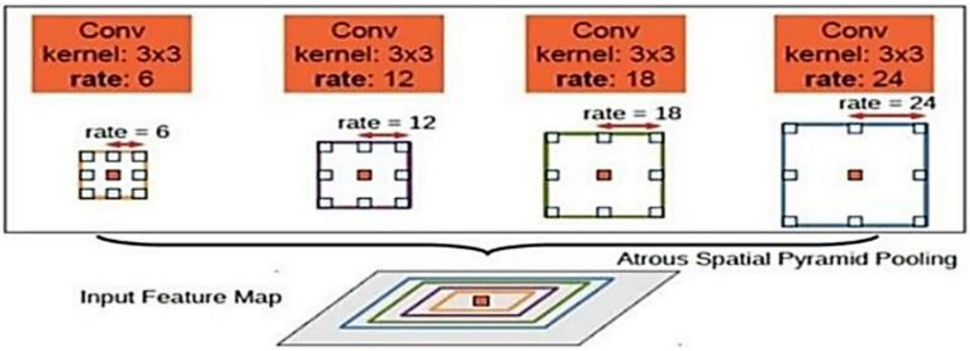

Fig. 7. ATROUS Spatial Pyramid module

In Fig. 7. using the different dilated rates of 6, 12, 18 and 24 with a kernel size 3x3 here parameters are same as 3x3 kernel. In ASPP these are connected in parallel for extracting the multi-scale feature information and fused together to boost the performance.

H. Performance Matrix

To evaluate the performance of data mining techniques, two evaluation measures were used, namely mean accuracy and IoU. The accuracy measure breaks down the following components:

- True Positive (TP): Pixels that were accurately identified as being in the target class.
- True Negative (TN): Accurately identified pixels that do not correspond to the specified category.
- False Positive (FP): Pixels that were mistakenly identified as being in the target class.
- False Negative (FN): False positives for pixels that should have been in the target class.

Accuracy: The proportion of accurately anticipated cases (both positive and negative) to total instances is the accuracy. Accuracy calculates as equ.4:

cc

IOU: IOU is a measure that compares the amount of overlap and union among the forecast segmentation and the ground truth, or the area of overlap divided by the area of union. It is a way to evaluate how well the predictions match the ground truth [36]. The accuracy of the forecast declines as the IOU falls. Accuracy and IOU for specific classes. The IoU is calculated as equ.5.

$$\mathrm{IoU} = \frac{TP}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN}} \dots\dots\dots (5)$$

The following performance measures evaluate the performance of data mining techniques.

IV. RESULTS AND DISCUSSION

The outcomes of the approach for analyzing civil engineering structures using data mining methods are presented in this section. This research presents a deep learning-based automated civil infrastructure inspection system that can identify and quantify "Delamination," "Crack," and "Background" areas on actual structures down to the pixel level. The broad range of adaptability was achieved by building the training and validation datasets using photos collected from the Internet, on-field bridge inspection, and Google Street View under uncontrolled conditions. It is necessary to set up the model hyperparameters, dataset, and model architectures before beginning the training process. Since these parameters are not part of the networks themselves, heuristics are required to configure them rather than direct data estimation. We have therefore investigated the best possible network design with the following parameters: 10 epochs fixed, 16 pictures for the mini-batch, momentum 0.9, and L2 regularisation 0.0001. The training processes of each network (ResNet-18 to ResNet-50) have been investigated using values of 10^3 and 10^5 in order to determine an appropriate starting learning rate. The accuracy and IOU metrics for the "Background" class have likewise seen a little decline.

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Table II. Accuracy during Training Processes with 0.0001 Learning Rate

Iteration	ResNet-18 Accuracy (%)	ResNet-50 Accuracy (%)
125	80	79
250	83	82
375	84	83
500	84	84
625	84	84
750	84	84
875	84	84
1000	84	84
1125	84	84
1250	84	84

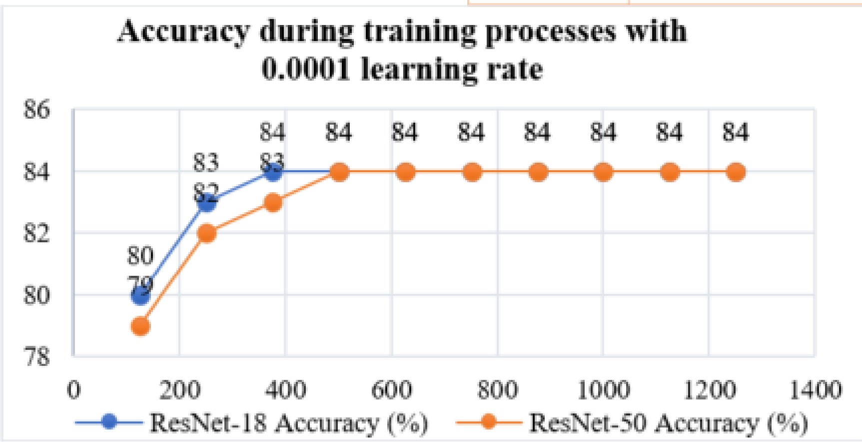

Fig. 8. Validation accuracy during training processes during training processes with 0.0001 learning rate.

Table 2 and Figure 8 show the accuracy progression during the training process of the ResNet-18 and ResNet-50 models with a learning rate of 0.0001. As the iterations increase, both models demonstrate gradual improvements in accuracy, reaching a plateau around the 500th iteration. By the 1250th iteration, the accuracy for both ResNet-18 and ResNet-50 stabilizes at 84%, indicating that the models have converged to an optimal solution. The validation accuracy (as depicted in Figure 8) further corroborates this steady progression, confirming that the models are effectively learning to identify structural defects.

Table III. Accuracy and IOU for Resnet-18 Network

	Accuracy	IOU
Delamination	0.893	0.654
Crack	0.850	0.243
Background	0.887	0.875

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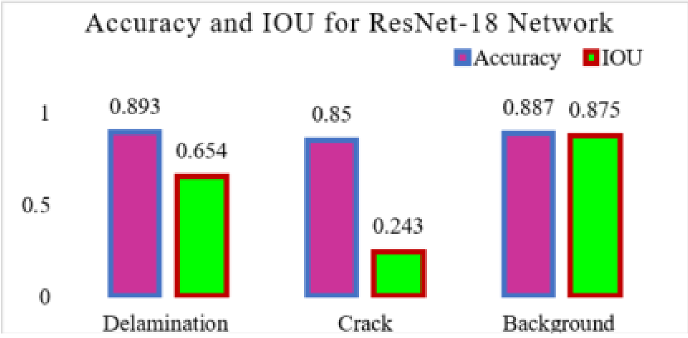

Fig. 9. Accuracy and IOU for Res-Net-18 Network

Table 3 shows the accuracy and IoU for the ResNet-18 network. The model performs best in detecting "Delamination" with an accuracy of 89.3% and an IoU of 0.654, followed by "Background" with 88.7% accuracy and an IoU of 0.875. "Crack" detection is the most challenging, with an accuracy of 85.0% and an IoU of 0.243. Figure 11 visualizes these metrics, highlighting the network's strengths in delamination and background detection, but indicating the need for improvement in crack segmentation.

Table IV. Accuracy and IOU for Resnet-50 Network

	Accuracy	**IOU**
Delamination	0.917	0.659
Crack	0.883	0.243
Background	0.882	0.873

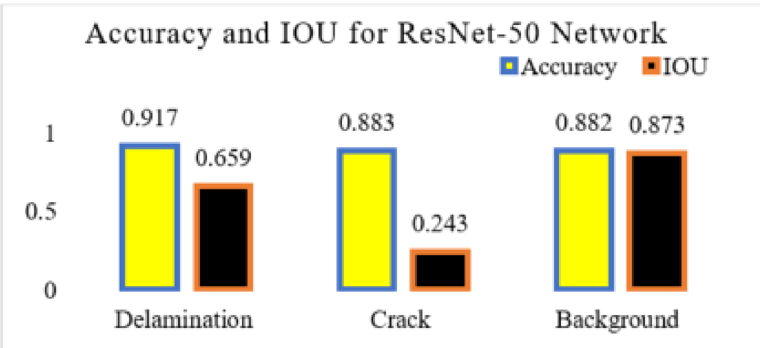

Fig. 10. Accuracy and IOU for Res-Net-50 Network

The table 4 and Figure 10 depicts the accuracy and IOU for Res-Net-50 Network here X axis shows the delamination, crack, and background while Y axis shows the metric. The ResNet-50 Network was selected as the reference design in this study because to the significant improvements in mean accuracy (from 0.87739 to 0.89427, or around 1.7%) and mean IOU (from 0.5909 to 0.59213).

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Fig. 11.Examples of detection results by the network

Figure 11 displays some of the network's detection findings, showing how well the model can detect and categorize bridge infrastructure problems, including fractures and delamination. These results highlight the effectiveness of the network in real-world scenarios.

Fig. 12.Test images with high-resolution pier cap(e), abutment(f), pier cap(g), and concrete surface (h).

Figure 12 presents high-resolution test images, including a pier cap (e), abutment (f), another pier cap (g), and a concrete surface (h), utilized to evaluate a model's performance. These images provide a detailed view of various structural components, offering insights into the model's ability to handle diverse and complex structural conditions.

Table V. Area Measurement on Test Images

Figure	Delamination [px]	Crack [px]	Background [px]
E	765,182	50,047	3,939,521
F	190,094	2222	657,644
G	251,914	4280	1,292,598
H	0	27,957	3,711,667

Table 5 presents the area measurements for different structural defects in the test images. For image E, the area of delamination is 765,182 pixels, with a relatively small crack area of 50,047 pixels, and the background occupies 3,939,521 pixels. In image F, delamination covers 190,094 pixels, cracks are minimal at 2,222 pixels, and the background area is 657,644 pixels. In image G, the delamination area is 251,914 pixels, cracks are 4,280 pixels, and the background is 1,292,598 pixels. In image H, there is no detected delamination, but cracks cover 27,957 pixels, while the background area is large at 3,711,667 pixels. These measurements provide a quantitative assessment of defect distribution, highlighting the varying prominence of delamination, cracks, and background across different test images.

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V. CONCLUSION AND FUTURE SCOPE

The results of this research show that semantic segmentation based on deep learning is an excellent data mining technique for automatically detecting and analyzing bridge infrastructure structural faults. By leveraging diverse datasets, data augmentation, and advanced segmentation techniques like DeepLabV3+ with ResNet encoders, the methodology achieves high accuracy and robustness in detecting cracks and delamination under varying conditions. The ResNet-50 model, in particular, delivers exceptional performance with a validation accuracy of 91.04%. This work offers a scalable, cost-effective solution for infrastructure monitoring, providing a reliable tool for proactive maintenance and improving the long-term safety and sustainability of civil engineering systems. It is anticipated that the major focus of future research will be on improving semantic segmentation measures. In order to do this, we will make use of a more extensive dataset as well as multispectral photos, which offer more information concerning individual pixels. In addition, the information obtained from LiDAR sensors and digital models will be merged in order to facilitate the development of an evaluation strategy that is conducted in an entirely automated fashion. The result of this is that it is anticipated that computer vision-based approaches will soon leave conventional eye examinations obsolete. This is owing to the fact that these methods offer an objective evaluation and are efficient in terms of the utilization of resources.

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