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Crack Detection Model in Buildings and Bridges Via Computer Vision Technique with Artificial Intelligence (AI) – Recent Advances, Challenges and Future Direction

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***Abstract:** As the fourth scientific and technological revolution approaches, artificial intelligence (AI) technology is subversively redefining social production and human life. The planning, design, building, maintenance, and management of civil infrastructures have all incorporated it extensively. Within the vision-based community, scientists have focused on utilising deep learning techniques, which are integral to artificial intelligence, to analyse and manage the massive volume of monitoring data. In this study, we evaluate methods for crack detection that have been developed using image processing and Artificial Intelligence. For this purpose, numerous research articles from prestigious conferences and journals were obtained, and the corresponding crack detection methods for the proposed technique were examined, including their features, performance, dataset details, and the specific component to which the process is applicable. The outcome and accompanying constraints of every method are recorded. A comparative analysis of various techniques is carried out to identify the challenges and promising approaches for automatic crack detection in buildings and bridges.*

***Keywords**: Crack Detection, Computer Vision, Artificial Intelligence, Convolutional Neural Network, Image Segmentation in Buildings.*

Abbreviations:
IPTs: Image-Processing Techniques
ICM: Iterative Clipping Method
NDHM: Neighbouring Difference Histogram Method
CTA: Conditional Texture Anisotropy
FFA: Free-Form Anisotropy
LBP: Local Binary Pattern
BTH: Black Top-Hat
CNN: Convolutional Neural Network
DL: Deep Learning
FCN: Fully Convolutional Network
VVS: Virtual Visual Sensors
SHM: Structural Health Monitoring
DSN: Deeply-Supervised Nets
CIS: Crack Image Segmentation
ROI: Regions of Interest
DBN: Deep Belief Network
UAV: Unmanned Aerial Vehicle
RNNs: Recurrent Neural Networks
ML: Machine Learning
SVM: Support Vector Machines
ICM: Iterative Clipping Method
DSN: Deeply-Supervised Nets
GF: Guided Filtering

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I. INTRODUCTION

Construction firms are implementing new technologies to automate various processes at all stages, thereby lowering the accident rate, enhancing facility functionality, reducing labour costs, shortening the construction period, and ultimately reaping financial rewards. (ur Rehman et al., 2022). An increasing number of dams, bridges, tunnels, and other infrastructure projects are being completed as a result of China's ongoing economic development. (Sharma, 2019) [34]. The structural identification of this infrastructure has become a significant topic in the field of industrial manufacturing research, as its growth is expected to cause several construction-related issues. (Jiao et al., 2019) [18]. The majority of modern building structures are made of concrete, and as time passes, fissures of varying degrees frequently appear on the surface of the concrete. The building's life, service life, and other attributes can be deduced from the shape of this crack. (Chen & Zhao, 2017) [6]. Excessive load, uneven force, temperature changes and climate conditions, as well as the quality of construction and materials used, are the primary causes of cracks in structures. (Hoła et al., 2019) [15].

To identify abnormalities as a clear indication of possible flaws, it is crucial to monitor and maintain structural health, including the detection of surface cracks. The early detection of potential physical flaws in various man-made structures, such as buildings, bridges, dams, and large machinery like windmills and turbines, can be significantly aided by automatic crack detection. Although crack detection has been used for a long time, manual processes must be converted to automated ones due to technological advancements and innovative monitoring. Automation would speed up inspections while lowering expenses and reducing human error. The issue has already been addressed by various image-processing techniques (IPTs) (Kaseko & Ritchie, 1993; Liu et al., 2019; Zou et al., 2012). While these methods helped identify features, they struggled to differentiate samples with actual cracks due to lighting effects, edges, and shadows. Moreover, these methods are not adaptable to various image types and formats. Researchers and inspectors have recognised surface cracks as computer vision issues that can be resolved through deep learning methods since they are visual abnormalities.

The primary issue with traditional crack detection methods is how to handle noise caused by spots, stains, blurring, uneven lighting, and various scene conditions. Specific techniques assume that noise and fractures can be distinguished clearly. For example, the Iterative Clipping Method (ICM) thought that the intensities along cracks were often darker than those of their surroundings (Oh et al., 1998). Using a globally adjusted threshold, Li and Liu (2008) introduced the Neighbouring Difference Histogram Method (NDHM) for crack picture segmentation. However, when the test image contains numerous shadows and dark areas, the assumption above fails. Although these techniques demonstrated exceptional recall and precision rates, they are overly complicated and time-consuming. Some methods, such as Conditional Texture Anisotropy (CTA) and Free-Form Anisotropy (FFA), as measured by Nguyen et al. (2011), assess the texture anisotropy of the image, taking into account both brightness and connectivity. These methods demonstrated promising results in crack segmentation, but they were sensitive to edges, which can occasionally enhance noise. Saliency-based techniques, as proposed by Xu et al. (2013), are then employed to reduce noise. To obtain satisfactory crack segmentation results, Zhao et al. (2013) employed the Local Binary Pattern (LBP) approach to examine the fundamental local characteristics; however, each image requires a distinct set of parameters. Zhang et al. (2014) suggested employing the threshold segmentation method and the Black Top-Hat (BTH) transformation to identify cracks in concrete tunnel surface photos; however, their approach may not be practical in photos with uneven lighting.

II. CRACK DETECTION MODELS

For several decades, the most popular and conventional method for detecting cracks in concrete structures was manual inspection. However, manual inspection is inaccurate and inefficient. Furthermore, this method is time-consuming, complex, and costly because it relies on inspectors' human vision to detect cracks while they walk along concrete structures. (Khan et al., 2023) [19]. Experienced inspectors perform manual inspections, which require a significant amount of time and depend on their subjective and empirical expertise. Delays caused by this drawn-out procedure further jeopardise the structural integrity of the infrastructure. (Golding et al., 2022) [12]. With the development of automated technology and the recognition of the limitations of manual inspection, Golding et al. (2022) propose a convolutional neural network (CNN)-based deep learning (DL) approach for autonomous crack detection, aiming to overcome the manual restrictions.

With a focus on crack detection, classification, and measurement of crack length and width, researchers have investigated the automation of crack detection in concrete infrastructures. (Golding et al., 2022). The most popular techniques for crack identification are machine learning (ML) (convolutional neural network (CNN), fully convolutional network (FCN), random forest, etc). Hsieh and Tsai (2020) [16]; (Khan et al., 2021) [20] and image-based (thresholding, filtering, morphological, skeletonisation, etc.) (Mohan & Poobal, 2018) [29]. Because neural networks can automatically extract necessary features from concrete images and detect cracks more accurately, researchers are increasingly willing to use machine learning (ML) and deep learning (DL)-based classifier algorithms, such as Support Vector Machine (SVM), Sari et al. (2019) [33], Random Forest Shi et al. (2016) [35] Convolutional Neural Networks (CNNs) Yusof et al. (2019) [42] Recurrent Neural Networks (RNNs) Zhang et al. (2021) [44], etc., to further improve crack detection.

A. Computer Vision-Based Technique

In various applications, image processing techniques have been widely employed for crack detection. The basic premise of an image processing method for crack detection is to obtain high-quality photos using a camera, smartphone, unmanned aerial vehicle (UAV), or other imaging equipment. Preprocessing techniques, such as scaling, denoising, segmentation, and morphological processing, come next, all of which aim to eliminate shadows and prepare the image for crack detection. (Liu et al., 2015). As a non-contact and economical method for monitoring structural systems, video-based structural health monitoring (SHM) techniques have gained popularity. To record the dynamics of structures during their dynamic response, these methods utilise video technology. (Shariati et al., 2014). Virtual visual sensors (VVS) can be used to identify the fundamental frequency of vibration by analysing changes in pixel brightness caused by structural vibrations. (Zimmermann et al., 2016) [46]. Video technology has been combined with various optical measurement techniques to enhance spatial density and data accuracy. (HEATON, 2016) [14]. Artificial intelligence systems and high-speed cameras can detect structural degradation in real time. (Medhi et al., 2019) [28]. In laboratory tests, as well as in real-world monitoring instances of bridges and other civil structures, these video-based SHM approaches have demonstrated encouraging outcomes. (Dworakowski et al., 2016 [11]; Fukuda et al., 2013; Xu & Brownjohn, 2018) [39]. These methods, if improved, have the potential to transform structural health monitoring and seismic engineering by providing valuable information for building maintenance and repair.

B. Image Segmentation In Crack Building

In practice, automatically detecting cracks in pictures of various scenes is a helpful yet challenging task. Liu et al. (2019) present a deep hierarchical convolutional neural network (CNN) as an end-to-end method for pixel-wise crack segmentation prediction. DeepCrack is made up of Deeply-Supervised Nets (DSN) and Extended Fully Convolutional Networks (FCN). One of the primary indicators of ageing transportation infrastructure is the presence of cracks. Identifying and repairing fractures is crucial to ensuring the overall safety of the transportation system. Many studies have focused on creating pixel-level crack image segmentation (CIS) models based on deep learning (DL) to enhance crack detection accuracy, due to the remarkable performance of DL in this field. (Li et al., 2022) [24].

Semantic Segmentation divides each pixel in the picture into classes (such as wall and crack), whereas localisation and classification algorithms just display an object's position. (Ko et al., 2023). Since object detection algorithms identify each object and its location, but not its shape or size, they are superior to the previous two. The most effective method among the four is instance segmentation, as it provides details about the size, shape, and location of each item. (Ko et al., 2023). To extract segmentation, edge, and background characteristics, use the Retinex and Prewitt filters. After that, a Deep Belief Network (DBN) classifier was trained on the features. (Bengio, 2009). CNN-based methods are the most widely used classifiers in the AI space for identifying and detecting pavement cracks and potholes [31]. (Bhowmick et al., 2020 [5]; Silva et al., 2020) [36]. (Krizhevsky et al., 2017 [22] Silva et al. (2020) used the YOLO-v4 classifier to identify and categorise pavement cracks and potholes. To employ an AlexNet strategy based on CNN. 172 To conduct additional inspections of the welding sites, three concentrated on confirming Regions of Interest (ROI) surrounding bridge metal joints (Yeum et al., 2019) [41]. (Dorafshan et al., 2017) [9] Demonstrated the superiority of AI-based techniques for crack identification by contrasting the CNN approach's performance with that of conventional image processing filters. A two-step deep learning technique for the automatic detection of façade cracks was proposed by Chen et al. (2021) [7].

C. Artificial Intelligence Technique

i. Machine Learning

Predicting the mechanical characteristics of various building materials is currently a key area of focus for the application of machine learning techniques in the construction sector. (Beskopylny et al., 2023) [3]. In the future, systems for forecasting the operational attributes of goods, buildings, and facilities will be based on artificial intelligence-infused algorithms, utilising the features of the original components and process parameters. Artificial intelligence techniques, including the creation, training, and use of specialised algorithms to ascertain the properties of the resultant concrete, can be used to enhance the manufacture of concrete. (Beskopylny et al., 2022) [4].

To begin, a dataset including surface fractures that the machine learning model is to identify must be gathered. A previous study conducted by Lin et al. used 30,000 low-resolution pictures. (Yang et al., 2018) [40]. Using image processing techniques, the photos are preprocessed to eliminate shadows, lower noise, and change other aspects of the pictures, including brightness and size. Pixel−by−pixel annotation, also known as labelling, is the process by which the image's cracked pixels are identified. Either a labelling instrument or physical labour might be used for this phase. One way to label an image is to set the pixels that have cracks as white, or "1," and the remaining pixels as black, or "0." Following this stage, a machine learning model must be chosen for application to crack detection. Crack detection has previously been studied using a variety of machine learning models, including CNN, support vector machines (SVM), and decision trees. (Salman et al., 2013).

D. Convolutional Neural Network (CNN) Algorithm

The convolutional neural network model has been used to amplify and extract the features of the data and previous studies to propose the building crack detection models of FCN (Fully Convolutional Networks), R-CNN (Regions with CNN feature), and RFCN (Richer Fully Convolutional Networks) to address the damage caused by the concrete structure, which reduces the life of infrastructure, endangers pedestrian safety, and has a profound impact on the social economy (R. Ali et al., 2022 [2]; Zheng et al., 2020). The model is assessed in terms of morphological and geometric indexes through the training of building surface data, including buildings, bridges, roads, and dams (Zheng et al., 2020) [45]. (Beskopylny et al., 2023) [21] used a YOLOv4 convolutional neural network for detecting cracks in samples of construction materials and boosted the quantity of photos by using our enhancement algorithm. It was done to optimise the intellectual model's parameters using the YOLOv4 convolutional neural network. In the world, the majority of buildings are made of masonry. Currently, the structural condition of the majority of these structures is examined by hand, which is a time-consuming, expensive, and subjective procedure. Advances in computer vision offer the opportunity to automate the visual inspection process using digital images (Dais et al., 2021) [8]. Based on the convolutional neural network model to amplify and extract the features of the data, building crack detection models of FCN (Fully Convolutional Networks), R−CNN (Regions with CNN feature), and RFCN (Richer Fully Convolutional Networks) have been proposed to address the damage caused by the concrete structure, which reduces the life of infrastructure, endangers pedestrian safety, and has a profound impact on the social economy (Zheng et al., 2020). By using feature frame extraction, R-CNN significantly reduces the reliance on the conventional one-by-one enumeration approach compared to the CNN network, and the detection speed is comparatively quick. This is consistent with the report and has been confirmed in the preliminary experiments. The quicker R-CNN is found to be able to automatically locate the raw crack image, demonstrating the validity of the R-CNN neural network model. In contrast to CNN, FCN concentrates on classifying visual pixels (Hoła et al., 2019). Any image can be entered into the neural network model based on image segmentation. Thanks to the advancement of image segmentation technology, crack recognition accuracy is higher than that of conventional approaches (Sorensen et al., 2019) [37]. The findings demonstrate that the FCN model's detection accuracy is 91% across a range of threshold values. He discovered that the average accuracy of the model is almost 90% and that the fracture density can be reasonably estimated after applying the FCN network model to concrete. (Dung, 2019) [10].

Table 1. Summary of the CNN Algorithm

References	Proposed Algorithms	Results
(Beskopylny et al., 2023)	YOLOv4	According to experimental findings, the Yolov4 model created in this article is exact regarding defect identification issues (AP@50 = 85% and AP@75 = 68%).
(Dais et al., 2021)	CNN	Crack detection on brick surfaces is carried out on a patch level with 95.3% accuracy and on a pixel level with 79.6% F1 score by utilising the effect of transfer learning.

III. BUILDING AND BRIDGES ANOMALIES

Building inspections require a significant amount of time and are typically repeated every five to ten years, depending on the maintenance plan. (Ismail, 2017) [17]. For the most part, inspections are done manually by inspectors. When applied to large structures (or a portfolio of properties), it is a labour-intensive operation. Furthermore, if high-rise buildings must have their exteriors inspected, this could be hazardous because, traditionally, an inspector must rappel down across several sides of the building. (Li et al., 2022). Furthermore, skilled workers performing manual visual examinations typically use specialised surveying instruments, such as crack rulers and magnifiers. Results can occasionally be erratic and subject to bias. (Parente et al., 2022) [30]. As a result, consistent computerised data—that is, digital data—that can be utilised to compare the outcomes of subsequent inspections across time is not left behind by the manual inspection.

The primary issue with traditional crack detection methods is how to handle noise caused by spots, stains, blurring, uneven lighting, and varying scene conditions. Specific techniques presume that noise and fractures can be distinguished clearly. For example, the Iterative Clipping Method (ICM) assumed that the intensities along cracks were often darker than those of their surroundings (Oh et al., 1998). Using a globally adjusted threshold, Li and Liu (2008) introduced the Neighbouring Difference Histogram Method (NDHM) for crack picture segmentation. However, when the test image contains numerous shadows and dark areas, the assumption above fails. Although these techniques demonstrated exceptional recall and precision rates, they are overly complicated and time-consuming. Some methods, such as Conditional Texture Anisotropy (CTA) and Free-Form Anisotropy (FFA), as measured by Nguyen et al. (2011), assess the texture anisotropy of the image, taking into account both brightness and connectivity. These methods demonstrated promising results in crack segmentation, but they were sensitive to edges, which can occasionally enhance noise. Saliency-based techniques, as proposed by Xu et al. (2013), are then employed to reduce noise. To obtain satisfactory crack segmentation results, Zhao et al. (2013) employed the Local Binary Pattern (LBP) approach to examine the fundamental local characteristics; however, each image requires a distinct set of parameters. Zhang et al. (2014) suggested employing the threshold segmentation method and the Black Top-Hat (BTH) transformation to identify cracks in concrete tunnel surface photos; however, their approach may not be practical in photos with uneven lighting.

Road networks, roads, bridges, dams, and other infrastructure are essential components of any community. The dependability of structures can be negatively impacted by structural flaws resulting from ageing and environmental changes, underscoring the importance of infrastructure monitoring techniques. (Hamishebahar et al., 2022) [13].

A. Advanced AI Models for Crack Detection

As deep learning has advanced, several techniques that utilise CNNs to detect cracks have emerged one after the other. In contrast to pixel-wise segmentation, specific approaches by Mandal et al. (2018), and Zhang et al. (2016) [43] Employed CNNs as classifiers to predict a label for each local patch. Furthermore, it is challenging to compare the effectiveness of the aforementioned conventional techniques with CNN-based techniques because neither has released an open dataset for crack detection. As illustrated in Figure 1, we investigate each level layer's significant aspects in the manner described below: (1) using feature maps of each convolutional stage to predict crack segmentation results (referred to as side output); (2) concatenating all side outputs to create a final fused result; (3) using Deeply-Supervised Nets (DSN) Lee et al. (2015) to supervise both side outputs and fused results, forming an integrated direct supervision; and (4) applying Guided Filtering (GF) to refine the final fused result (He et al., 2012). When used for crack detection, parallel architectures such as HED produced state-of-the-art results (Xie & Tu, 2015). The primary focus of this article is DeepCrack, which fully utilises sophisticated techniques to achieve a deep, end-to-end, and pixel-wise crack segmentation architecture. Furthermore, we developed an open benchmark that manually annotates multi-scale and multi-scene cracks to assess the crack detection methods. (Liu et al., 2019).

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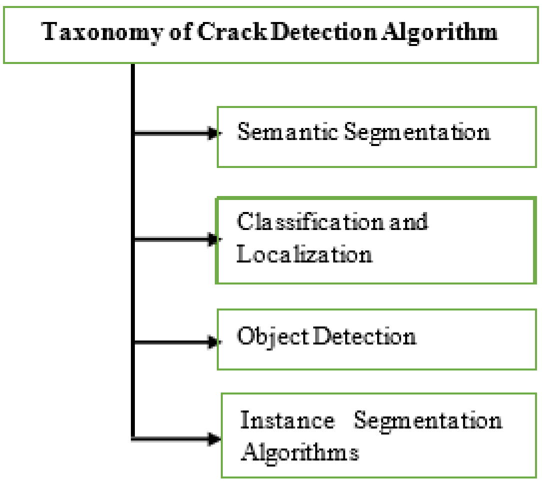
IV. RECENT DEVELOPMENT – NEW APPROACHES IN CRACK DETECTION

To produce unique building materials, patterns, and hidden relationships between technological and physical parameters can be found. Additionally, mechanical properties can be predicted, and the problem of detecting, classifying, and segmenting existing defects can be resolved through the creation and training of artificial neural networks with a given accuracy (Beskopylny et al., 2023). Another innovative method uses portable device photos to provide a comprehensive automated fracture identification and crack depth evaluation framework for concrete structures through: firstly, to automatically identify cracks on a concrete surface, a binary-class Convolutional Neural Network (CNN) model was created, secondly, automatically detected the depth of the fractures, an integrated CNN model was developed by merging the convolutional feature extraction layers with regression models (RF and XGBoost) (Laxman et al., 2023) [23]. Finding flaws of all kinds in construction material components early in the manufacturing process helps enhance construction quality and pinpoint the source of specific harm. To prevent the spread of faulty materials and facilitate building monitoring, identifying cracks in samples of building materials is crucial (Beskopylny et al., 2023). In Li et al. (2022), the hyperparameters of the suggested model were adjusted to achieve the highest fracture detection accuracy with the least computational cost. For hassle-free civil structure monitoring, the proposed model enables the use of deep learning techniques with low-power computing equipment.



[Fig.1: Taxonomy of the Crack Detection Algorithm]

V. TERMINOLOGY FOR SEARCHES

One of the most efficient search keywords was established by carefully and methodically choosing the core search terms. A significant research paper used the following keywords in a reliable academic database: Crack detection, AI and Deep Learning, vision-based, and Crack detection using AI and Deep Learning.

Table-II: Summary of Search Terms

S/N	Sources of Academic Papers	Domain Site	No. of Review Papers
1.	Springer	http://www.springer.com/	17
2.	IEEE	http://www.ieeexplore.ieee. org/	14
3.	Explore Science	http://www.sciencedirect.co m/	16
4.	Google	http://www.scholars.google. com/	34
	Scholar	**Total of Review Papers**	66

A. Challenges and Future Direction

Deep learning methodologies are expanding swiftly and have been utilised in numerous structural health monitoring applications, including structural damage identification and condition evaluation. Nonetheless, certain theoretical and technical obstacles persist in hindering the widespread use of deep learning-based methodologies for the structural health monitoring of civil infrastructures (Ye et al., 2019) [25]. The following significant issues are outlined:

i. Deploying deep learning-based techniques for crack detection in buildings becomes more Expensive due to the need for high-performance hardware. It requires a significant amount of data and Repetitive training to train a DNN properly. Large-volume hard drives are needed to store the vast amounts of data, particularly pictures and videos. A large-capacity memory, numerous GPUs, and a CPU are required to implement the training process. Additional equipment for processing and storing data is required, including servers, cloud computing platforms, or high-performance workstations.

ii. In deep architecture, over-fitting is another issue that must be resolved when millions of parameters are to be changed. For example, insufficient training samples for structural damage identification will result in the excessive extraction of extraneous features, such as background noise. Expanding strategies to increase the number of samples won't be effective if the training samples don't accurately represent real-world scenarios, particularly in the case of image-based structural damage identification in various environmental circumstances.

iii. The dataset plays a crucial role in a DNN's training procedure. For instance, a VGG-16 needs thousands of annotated images for training to modify its more than 100 million parameters for crack detection.

The use of AI techniques for crack identification has skyrocketed in recent years. It becomes challenging for an AI to complete a crack-recognition task since cracks are uneven in shape and lack a defined size. (Piryonesi &

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El-Diraby, 2020) [32]. Furthermore, the domain under consideration presents additional challenges that must be addressed for the AI algorithms to simulate human perceptions accurately. (Wen et al., 2022) [38]. Numerous AI-based fracture detection studies utilising 3D images have also been conducted in recent years. (Wen et al., 2022). Modern AI techniques can also be enhanced to incorporate new crack features, such as crack dimensions, and adapt to 3D imaging technology to improve model generalisation capabilities. (L. Ali et al., 2022) [1] Determining the crack's dimensions will assist authorities in selecting how best to use the structure in addition to assessing the crack's severity. The goal of crack detection is to employ vision-based methods to record the current condition of the structures. (Mamlouk et al., 2018) [26].

There is limited research on crack detection that utilises a continuous mosaic to create a composite image of the structure. The combination of close-range and aerial, as well as satellite, photographs must be taken into account to provide inspectors with a more comprehensive picture of the fracture density of the structures. Aerial and satellite photos can offer a more affordable option in places where heavy traffic or other environmental conditions make it impossible to take pictures with a drone or handheld cameras. (Wen et al., 2022).

VI. CONCLUSION

In this study, we evaluate methods for crack detection that have been developed using image processing and Artificial Intelligence. For this purpose, numerous research articles from prestigious conferences and journals were obtained, and the corresponding crack detection methods were examined about the proposed crack detection technique, including its features, performance, dataset details, and the specific component to which the process is applicable. The outcomes and accompanying constraints of every method are recorded. A comparative analysis of various techniques is carried out to identify the challenges and promising approaches for automatic fracture identification.

APPENDIX

It is optional. Appendices, if needed, appear before the acknowledgement.

ACKNOWLEDGMENT

It is optional. The preferred spelling of the word "acknowledgement" in American English is without an "e" after the "g." Use the singular heading even if you have many acknowledgements. Avoid expressions such as "One of us (S.B.A.) would like to thank" Instead, write "F. A. The author thanks" Sponsor and financial support acknowledgements are placed in the unnumbered footnote on the first page.

DECLARATION STATEMENT

I must verify the accuracy of the following information as the article's author.

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