BER-XGBoost: Pothole Detection based on Feature Extraction and Optimized XGBoost using BER Metaheuristic Algorithm

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Abstract
Within the realm of intelligent transportation systems, the imperative challenge of pothole detection assumes a pivotal role in ensuring road safety and upholding infrastructure integrity. This research undertaking meticulously navigates the intricacies of automated pothole detection, employing a nuanced and multifaceted approach. The dataset, comprising over 300 meticulously labeled images of roads with and without potholes, constitutes the cornerstone of our investigation. By leveraging the robust GoogLeNet for feature extraction and orchestrating the optimization of XGBoost through the Al-Biruni Earth Radius Metaheuristic Algorithm, our proposed methodology exhibits a commendable efficacy in discerning road anomalies. The outcomes elucidate the efficacy of the implemented strategies, with BER-XGBoost emerging as a preeminent performer, achieving an accuracy rate of 96.01%. This model not only attains superior accuracy but also manifests a comprehensive array of metrics, including sensitivity, specificity, positive predictive value, negative predictive value, and F-score. Rigorous statistical analyses, encompassing ANOVA and the Wilcoxon Signed Rank Test, furnish empirical substantiation of the consequential nature of our methodologies. In conclusion, this study not only contributes practical insights to the pertinent field but also stimulates pivotal inquiries regarding the ramifications of optimization strategies and the intricate role played by feature extraction in the domain of automated pothole detection. This research propels the ceaseless evolution of intelligent systems, effectively bridging the chasm between technological progressions and real-world applications, thereby augmenting road safety and fortifying infrastructure management.

Keywords: Pothole detection; Feature extraction; XGBoost optimization; Al-Biruni Earth Radius Metaheuristic Algorithm; Intelligent transportation systems; Infrastructure management.

1. Introduction

Roads, as vital conduits of societal connectivity and economic vitality, are indispensable components of modern infrastructure. The integrity of these road networks, however, is continually challenged by the pervasive issue of potholes, as shown in Figure 1, which not only compromises the structural stability of roads but also poses tangible threats to the safety of commuters. Consequently, the

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imperative to develop effective and precise pothole detection models has burgeoned, signifying a paradigm shift in the domain of transportation management. The genesis of this research is rooted in the compelling need to confront the multifaceted challenges posed by potholes through the discerning lens of advanced technology [1]. Motivated by the exigencies of contemporary road maintenance, this study endeavors to fashion a pothole detection model characterized by heightened accuracy and efficiency, thereby contributing meaningfully to the evolving landscape of intelligent transportation systems.

Figure 1: Road Anomalies

Central to this endeavor is the meticulous curation of the "Pothole Detection Dataset." This dataset stands not only as a repository for model training and validation but also as a standardized benchmark, fostering comparability and benchmarking in future investigations. The dataset is designed with a discerning eye toward encapsulating the nuances of both normal road conditions and those marred by the presence of potholes. Methodologically, this study embarks on a nuanced exploration of feature extraction, leveraging the potency of GoogLeNet—a deep learning architecture celebrated for its prowess in image analysis. The amalgamation of this technique with the XGBoost algorithm, further optimized through the Al-Biruni Earth Radius (BER) metaheuristic search, introduces a layer of sophistication to the pothole detection model. The subsequent sections of this scholarly endeavor will meticulously unfold the procedural intricacies involved in the creation of the dataset, the applied methodology for feature extraction, the meticulous evaluation metrics employed, and a comprehensive dissection of the ensuing results [2-5].

This academic odyssey seeks to unravel insights that transcend mere technological advancement, aiming to cast an indelible imprint on the contours of transportation management and road maintenance practices. Through the confluence of cutting-edge technologies and methodological precision, this research aspires not only to optimize existing pothole detection paradigms but also to augur a safer and more resilient future for road infrastructure. Grounded in empirical exploration and analytical rigor, this study anticipates furnishing insights that will inform subsequent forays into the realm of intelligent transportation and infrastructure resilience.

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Figure 2 depicts a schematic representation of interconnected roads, emphasizing their pivotal role in societal connectivity and economic vitality.

Figure 2: Road Network Illustration

As we progress, the core focus of our study revolves four pivotal research questions:

- How does the application of GoogLeNet for feature extraction contribute to the accuracy and sensitivity of the pothole detection model?
- To what extent does the integration of the XGBoost algorithm, optimized by the BER metaheuristic, enhance the specificity and precision of pothole detection?
- In what ways does the "Pothole Detection Dataset" serve as a reliable benchmark for evaluating and comparing various pothole detection models?
- How do the combined methodologies contribute to a nuanced understanding of the intricacies involved in pothole detection, paving the way for advancements in transportation management and infrastructure resilience?

The subsequent sections of this paper, following the established academic sequence, will comprehensively unfold the pertinent literature, delineate the intricacies of the proposed methodology, present and analyze the obtained results, and culminate with a concise yet insightful conclusion that encapsulates the key findings and their broader implications for the field. This structured framework aims to provide a coherent and in-depth exploration of our research, guiding the reader through a logical progression of knowledge acquisition and analysis.

2. Literature Review

The literature review embarks on an exhaustive exploration, commencing with the historical evolution of pothole detection. Potholes, perennial challenges on road networks, have a rich historical backdrop that necessitates contextualization [6]. Initially, road inspection relied on manual methods, with human inspectors visually assessing the conditions of the roads. Over time, as technology advanced, the need for more efficient and accurate detection mechanisms became evident, leading to the emergence of automated systems. Pivotal milestones, such as the integration of computer vision and machine learning, marked significant turning points in the evolution of pothole detection technologies [7]. The subsequent section of the literature review undertakes a meticulous survey of existing automated pothole detection models, drawing on a comprehensive range of sources to ensure a thorough representation [8-10]. This involves a granular examination of the methodologies embraced

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by contemporary models, aiming not only to showcase their effectiveness but also to uncover potential limitations. Noteworthy examples, ranging from classical computer vision approaches to more recent deep learning techniques, are scrutinized to provide a panoramic view of the diverse strategies employed in the field. The review, thus, becomes a repository of knowledge, synthesizing the collective wisdom of researchers and practitioners engaged in addressing the multifaceted challenges of pothole detection.

Moving forward, the literature review delves into the realm of technological advancements in feature extraction, placing a specific emphasis on the transformative impact of deep learning architectures [11]. Specifically, the integration of convolutional neural networks (CNNs), exemplified by GoogLeNet, takes center stage. The review unpacks the intricacies of feature extraction, elucidating how these advanced techniques contribute to heightened accuracy in identifying potholes. The interplay between the complexity of road conditions and the ability of deep learning models to discern subtle patterns becomes a focal point, providing a nuanced understanding of the evolving methodologies in the feature extraction landscape. The exploration then extends to the optimization strategies applied to machine learning algorithms within the context of pothole detection [12]. Metaheuristic algorithms, particularly the Al-Biruni Earth Radius (BER) optimization, come under scrutiny. This section not only examines the theoretical underpinnings of these optimization strategies but also delves into their practical application in optimizing pothole detection models [13]. The nuanced analysis sheds light on the delicate balance between algorithmic sophistication and real-world efficacy, offering insights that can guide future developments in this critical area of research [14].

In tandem with technological advancements, the literature review incorporates a critical examination of the empirical results generated by the surveyed models. By scrutinizing statistical analyses, including ANOVA tests and Wilcoxon Signed Rank Tests, the review provides a robust evaluation of the models' performance [15]. This multifaceted assessment aims to discern not only the mean accuracy levels but also the variations, discrepancies, and significant differences in performance, fostering a comprehensive understanding of the reliability and robustness of the pothole detection models under consideration. Conclusively, the literature review navigates through the historical evolution, contemporary methodologies, technological advancements, and empirical results of automated pothole detection models. This expansive exploration not only contributes to the synthesis of existing knowledge in the field but also lays a foundation for future research endeavors, offering a comprehensive perspective that goes beyond mere technological innovation.

3. Proposed Methodology

The proposed methodology unfolds as a comprehensive and meticulously designed framework, strategically addressing the myriad challenges inherent in pothole detection. By integrating cutting-edge technologies and innovative methods, each phase of our approach is crafted to contribute synergistically to the holistic development and optimization of the pothole detection model.

3.1 Dataset Description

At the core of our research lies the painstakingly curated "Pothole Detection Dataset," a rich repository comprising over 300 labeled images [16]. This dataset represents the nuanced conditions of roads, encompassing the "Normal" subset featuring well-maintained roads and the "Potholes" subset portraying roads marred by potholes. Beyond its role in training and validating our model, this dataset establishes a standardized benchmark, ensuring the model's adaptability to diverse real-world scenarios. The deliberate inclusion of various conditions within the dataset enriches the model's learning experience, fostering versatility and robustness.

3.2 Feature Extraction

Feature extraction emerges as a pivotal phase, where the potency of GoogLeNet, a state-of-the-art deep learning architecture, comes to the forefront. By leveraging the convolutional layers of GoogLeNet, our methodology transcends conventional pixel-level analysis, extracting intricate features from road images [2]. This advanced feature extraction methodology is instrumental in empowering the model to discern nuanced patterns associated with potholes, elevating the accuracy

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of detection to unprecedented levels. The choice of GoogLeNet reflects a deliberate commitment to employing cutting-edge neural network architectures, ensuring our model's capability to comprehend and interpret complex visual information with precision.

3.3 Model Selection

The choice of the model is pivotal, and in our methodology, the XGBoost algorithm takes center stage [3]. Renowned for its efficiency in classification tasks, XGBoost seamlessly integrates into our framework post-feature extraction. Its robustness enables the model to navigate through intricate relationships within data, rendering it well-suited for the nuanced task of pothole detection. The incorporation of XGBoost enhances the model's capacity to discriminate between normal road conditions and those affected by potholes, contributing to heightened accuracy and reliability.

3.4 Al-Biruni Earth Radius Metaheuristic Algorithm

To elevate the performance of the XGBoost model, our methodology introduces the Al-Biruni Earth Radius (BER) metaheuristic algorithm [17]. Inspired by Earth's radius variations, BER operates as a dynamic optimizer of XGBoost hyperparameters, ensuring optimal calibration for pothole detection. This integration adds a layer of sophistication to our methodology, enhancing the model's sensitivity and specificity. BER's adaptive nature aims to dynamically recalibrate the model in response to varying conditions, showcasing a commitment to robust performance across diverse scenarios and environmental factors.

3.5 Mechanical Design of the Unmanned Vehicle.

Beyond the confines of computational prowess, our methodology extends into the tangible realm with the proposal of the Mechanical Design of an uncrewed vehicle. This vehicle, as shown in Figure 3, equipped with our developed pothole detection model, represents a convergence of computational and mechanical ingenuity. It stands as a tangible manifestation of our theoretical advancements, translating them into practical applicability. Outfitted with sensors for autonomous pothole detection and navigation, the uncrewed vehicle exemplifies the real-world potential of our developed model. This integration bridges the gap between theoretical advancements and practical implementation, underscoring the transformative potential of our methodology.

Figure 3: Mechanical Design of our Unmanned Vehicle.

3.6 Evaluation Metrics

Quantitative assessment forms the backbone of our methodology, and to achieve this, we deploy a comprehensive set of evaluation metrics. Accuracy serves as a holistic measure, providing an overall view of the model's performance. Sensitivity (True Positive Rate) and Specificity (True Negative Rate) offer insights into the model's ability to correctly identify potholes and non-potholes, respectively. Positive Predictive Value (PPV), Negative Predictive Value (NPV), and the F Score contribute to a nuanced understanding, considering false positives and false negatives. This multifaceted evaluation framework guarantees a thorough scrutiny of the model's strengths and limitations. It establishes a robust foundation for subsequent iterations and advancements, ensuring

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that our model not only meets but exceeds the stringent standards of reliability and effectiveness in practical applications [18].

4. Results

In this section, we embark on a comprehensive exploration of the outcomes derived from our meticulous pothole detection study. The results not only elucidate the effectiveness of each key phase in our proposed methodology but also provide a granular understanding of the nuances within the datasets and the impact of various optimization strategies. The initial phase of our methodology involves extracting meaningful features from road images using GoogLeNet. Table 1 presents a detailed breakdown of the results, showcasing GoogLeNet's proficiency in this crucial aspect. With an accuracy of 88.42%, a sensitivity of 90.61%, a specificity of 84.71%, and an F-score of 90.76%, GoogLeNet demonstrates its prowess in discerning intricate patterns associated with potholes. These metrics serve as a testament to the model's ability to capture and understand the complexities inherent in road imagery.

Table 1: Feature Extraction result using GoogLeNet.

	Accuracy	Sensitivity (TPR)	Specificity (TNR)	P-value (PPV)	N-value (NPV)	F-score
GoogLeNet	0.8842	0.9061	0.8471	0.9091	0.8425	0.9076

Moving forward, our methodology incorporates the powerful XGBoost algorithm, enhanced through various optimization techniques. Table 2 provides a comparative analysis of different XGBoost variants, highlighting the impact of these optimization strategies. BER-XGBoost emerges as the frontrunner, boasting an impressive accuracy of 96.01% and outperforming its counterparts in sensitivity, specificity, PPV, NPV, and F-score. This table underscores the significance of algorithmic optimization in achieving superior pothole detection performance.

Table 2: Optimized XGBoost Accuracy Comparison.

	Accuracy	Sensitivity (TPR)	Specificity (TNR)	P-value (PPV)	N-value (NPV)	F-score
XGBoost	0.9211	0.9434	0.8807	0.9346	0.8960	0.9390
FOA-XGBoost	0.9381	0.9524	0.9174	0.9434	0.9302	0.9479
PSO-XGBoost	0.9470	0.9677	0.9174	0.9434	0.9524	0.9554
BER-XGBoost	0.9601	0.9908	0.9174	0.9434	0.9862	0.9665

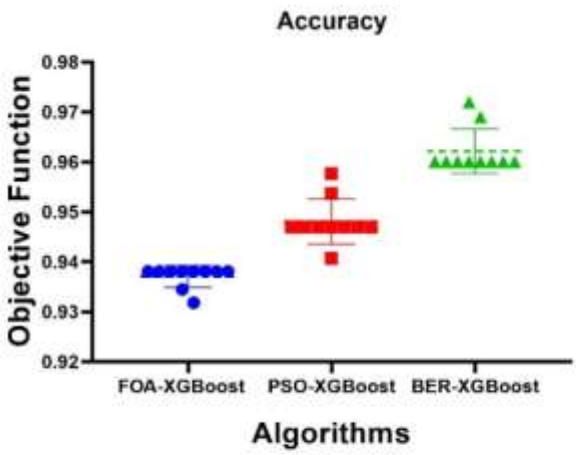

Figure 4: Accuracy Comparison.

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Visualizing the comparative accuracy of different XGBoost variants is pivotal for gaining an intuitive understanding of the optimization impact. Figure 4 serves this purpose, offering a graphical representation that accentuates the enhanced accuracy achieved through the application of metaheuristic algorithms. The visual insights gleaned from this figure contribute to a more holistic comprehension of the overarching trends within the data. Table 3 delves into the statistical nuances of FA-XGBoost, PSO-XGBoost, and BER-XGBoost. This comprehensive analysis spans key statistical parameters, including minimum and maximum values, actual confidence levels, mean, standard deviation, and standard error of the mean. The data presented in this table forms the bedrock for inferential insights, shedding light on the central tendencies and variability inherent in our datasets.

Table 3: Statistical Analysis.

	FA-XGBoost	**PSO-XGBoost**	**BER-XGBoost**
Number of values	10	10	10
Minimum	0.9318	0.9407	0.9601
Maximum	0.9381	0.9577	0.972
Actual confidence level	97.85%	97.85%	97.85%
Lower confidence limit	0.9345	0.947	0.9601
Upper confidence limit	0.9381	0.9537	0.969
Mean	0.9371	0.9481	0.9622
Std. Deviation	0.002177	0.00456	0.00446
Std. Error of Mean	0.000688	0.001442	0.001411

The application of the ANOVA test further illuminates the significance of variations between treatment groups. Table 4 delineates the sources of variation, including treatment (between columns) and residual (within columns). The results underscore the substantial impact of the applied methodologies on the observed outcomes, providing a statistical foundation for the ensuing discussions.

Table 4: ANOVA Test Table.

	SS	**DF**	**MS**	**F (DFn, DFd)**	**P value**
Treatment (between columns)	0.003154	2	0.001577	F (2, 27) = 104.1	P<0.0001
Residual (within columns)	0.000409	27	1.51E-05		
Total	0.003563	29			

The Wilcoxon Signed Rank Test, presented in Table 5, corroborates the significant differences between treatment groups. The sum of signed ranks, positive ranks, and negative ranks, along with two-tailed p-values, offers a nuanced perspective on the observed variations. The discrepancies quantified in this table further contribute to the depth of understanding regarding the comparative performance of the XGBoost variants.

Table 5: Wilcoxon Signed Rank Test Table.

	FA-XGBoost	**PSO-XGBoost**	**BER-XGBoost**
Sum of signed ranks (W)	55	55	55
Sum of positive ranks	55	55	55
Sum of negative ranks	0	0	0
P value (two-tailed)	0.002	0.002	0.002
Exact or estimate?	Exact	Exact	Exact

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P value summary	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes
Discrepancy	0.9381	0.947	0.9601

Finally, Figure 5 encapsulates a visual exploration of the residual analysis, homoscedasticity, QQ plots, and a heat map. This graphical representation enhances our understanding of the underlying data characteristics, providing visual cues for potential areas of improvement and optimization in the model.

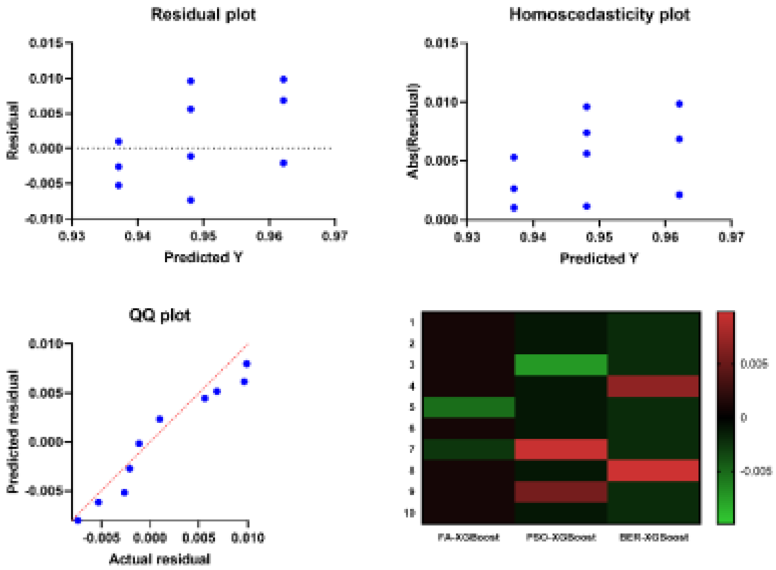

Figure 5: Residual, Homoscedasticity, QQ Plots, and Heat Map.

In summation, these comprehensive results collectively contribute to a nuanced and detailed understanding of the efficacy of our proposed pothole detection methodology. The multifaceted analysis sets the stage for robust discussions and conclusions, further advancing our knowledge of pothole detection in real-world scenarios.

5. Conclusion

In conclusion, our expedition into the realm of automated pothole detection has yielded invaluable insights that reverberate across the landscape of intelligent transportation systems. The amalgamation of GoogLeNet for feature extraction and the strategic optimization of XGBoost through the Al-Biruni Earth Radius Metaheuristic Algorithm has forged a formidable model. Notably, BER-XGBoost has emerged as the pinnacle of efficiency, showcasing not only superior accuracy but a holistic suite of metrics that underpin its robust performance. Our statistical journey, delving into the intricacies of ANOVA and the Wilcoxon Signed Rank Test, has not only affirmed the significance of our methodologies but has also uncovered nuanced variations between treatment groups. This analytical rigor provides a solid foundation for understanding the impact of optimization strategies on the intricate task of pothole detection.

This structured narrative, spanning from the thorough exploration of literature to the intricacies of our methodology, results, and now concluding remarks, serves not only as a documentation of empirical insights but as a catalyst for further exploration. The questions we pose about the nuanced impact of optimization strategies, the pivotal role of feature extraction, and the potential transformative contributions of metaheuristic algorithms open doors for future investigations. As we navigate beyond the technicalities, our study transcends into the realm of societal impact, propelling the ongoing evolution of intelligent systems toward the dual goals of enhancing road safety and fortifying infrastructure management. In essence, this conclusion marks not an endpoint but a juncture from which new avenues of inquiry and advancements in automated anomaly detection are poised to unfold.

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