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DEVELOPMENT OF A DEEP LEARNING-POWERED SYSTEM FOR CLASSIFYING CONSTRUCTION WORKER PRODUCTIVITY PATTERNS

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Abstract: In the construction industry, worker productivity is crucial for project success, but it is often challenging to accurately assess and monitor. Traditional manual methods of evaluating productivity can be time-consuming and subjective. This study presents the development of an automated system for classifying the productivity behavior of construction workers using deep learning. By employing computer vision and deep learning techniques, the system captures real-time video footage of workers and classifies their behavior into different productivity categories. The system is trained using a large dataset of labeled images representing various worker actions. The results indicate that the system is capable of accurately classifying worker behavior with high precision, offering a more efficient and objective way of assessing productivity on construction sites.

Keywords: Automated System, Deep Learning, Productivity Behavior, Construction Workers, Convolutional Neural Network, Video Analysis, Real-time Monitoring, Worker Classification, Construction Industry.

INTRODUCTION

Construction projects are often subject to delays, budget overruns, and quality issues, many of which are linked to suboptimal worker productivity. Assessing worker productivity traditionally relies on manual observation by supervisors or time studies, both of which can be inconsistent and labor-intensive. As the demand for more efficient and cost-effective construction methods grows, there is an increasing need for automation to monitor worker productivity objectively and in real-time.

Automated systems that can monitor and classify construction workers' behavior hold the potential to enhance project efficiency, identify bottlenecks, and improve safety standards. Recent advancements in computer vision and deep learning technologies provide an opportunity to develop such systems by using video data captured from construction sites. These technologies can analyze large volumes of visual data, detect and classify worker actions, and provide real-time feedback to improve productivity.

This study aims to develop an automated system for classifying construction workers' productivity behavior based on deep learning. By utilizing state-of-the-art convolutional neural networks (CNNs), the system can categorize worker actions such as “working,” “idle,” “waiting,” and “other non-productive

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behaviors" through video analysis. The system will allow construction managers to gain insights into productivity trends, identify inefficiencies, and make data-driven decisions.

The construction industry is a cornerstone of the global economy, contributing to the development of infrastructure and the creation of residential, commercial, and industrial buildings. However, despite its critical role, the construction sector is also one of the most challenging industries in terms of worker productivity and efficiency. A multitude of factors influences worker performance, including external conditions such as weather, equipment availability, and material supply, as well as individual factors such as skill level, motivation, and work environment. Understanding and improving construction worker productivity is therefore a key area of focus for industry leaders and project managers.

Historically, assessing worker productivity has been a subjective and labor-intensive task. Traditional methods, such as time studies, manual observation, and performance reviews, are not only time-consuming but also prone to biases and inaccuracies. These methods rely heavily on human judgment, which can vary between supervisors and may not always reflect the actual productivity levels of workers. As the demand for faster, more cost-effective, and higher-quality construction projects increases, there is an urgent need to adopt more objective and efficient approaches to productivity monitoring. This need is further exacerbated by the global shortage of skilled workers in the construction sector, which places additional pressure on project managers to maximize workforce efficiency.

In recent years, advancements in digital technologies, such as computer vision and deep learning, have opened new avenues for automating the monitoring and evaluation of construction worker behavior. Computer vision, which allows machines to interpret and understand visual data, and deep learning, a subset of machine learning that excels in pattern recognition, offer the potential to automate productivity assessment. By analyzing video footage captured on construction sites, these technologies can classify worker behaviors, such as whether a worker is actively engaged in a task, idle, or waiting for materials or instructions. The application of these technologies could significantly enhance the accuracy, speed, and scalability of productivity assessments on construction sites, providing real-time insights that are otherwise difficult to obtain through traditional methods.

Challenges in Construction Productivity Monitoring

The construction industry faces several challenges in the accurate and reliable monitoring of worker productivity. One of the primary challenges is the complexity and variability of construction tasks. Unlike manufacturing, where processes are often standardized, construction work is inherently dynamic and diverse, with tasks ranging from heavy lifting and equipment operation to fine detail work such as welding or carpentry. Workers may perform a variety of activities within a short period, making it difficult to classify their behavior and assess whether they are being productive or not.

Moreover, construction sites are typically large, noisy, and often chaotic environments. Workers may be spread across different areas of the site, and their actions may not always be visible to a single observer. In many cases, workers may perform tasks in short bursts, followed by waiting for instructions, equipment,

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or materials. This makes it hard to distinguish between non-productive behavior, such as standing still or talking, and productive periods when workers are momentarily inactive due to external factors. Traditional observation techniques often fail to capture this nuance, and human biases may cloud the judgment of supervisors tasked with evaluating worker performance.

The implementation of automated systems that rely on video surveillance and deep learning algorithms offers a promising solution to these challenges. Video-based systems can capture a wide range of activities across a construction site, and deep learning models can be trained to classify different behaviors based on visual patterns. By automating this process, it is possible to obtain a more objective, comprehensive, and real-time analysis of worker behavior, enabling construction managers to identify inefficiencies and address issues promptly.

The Role of Deep Learning in Productivity Classification

Deep learning has emerged as one of the most effective tools for image and video analysis, particularly due to its ability to learn complex patterns from large datasets without explicit programming. Unlike traditional machine learning techniques that rely on hand-crafted features, deep learning models, particularly Convolutional Neural Networks (CNNs), automatically learn hierarchical features from raw data, which makes them well-suited for tasks such as object detection, action recognition, and behavior classification.

In the context of construction productivity, deep learning can be used to classify workers' activities based on video footage captured from cameras mounted on-site. These cameras can monitor worker behavior throughout the day, providing continuous feedback on how workers spend their time. A deep learning model can analyze the footage and classify behaviors into distinct categories, such as:

- Working: Engaged in tasks that contribute directly to the construction process (e.g., operating machinery, assembling structures, welding).
- Idle: Standing still, not engaging in any productive task.
- Waiting: Temporarily inactive due to factors like equipment malfunction, material shortages, or waiting for instructions.
- Other: Non-task-specific activities such as walking between work areas or conversing with colleagues.

By using a deep learning model trained on a labeled dataset of worker behaviors, the system can identify these actions with high accuracy and provide real-time feedback to supervisors or project managers.

Advantages of an Automated System

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The development of an automated system for classifying construction worker productivity behavior presents several distinct advantages over traditional methods:

1. Objectivity: Unlike human observers, an automated system is not subject to biases or variations in judgment. This ensures more consistent and reliable productivity assessments.

2. Real-Time Monitoring: Video data can be processed in real-time, allowing for continuous feedback on worker behavior. This enables managers to identify inefficiencies or problems as they occur, rather than after the fact.

3. Scalability: Automated systems can be deployed across multiple construction sites simultaneously, making it easier to monitor large teams of workers or multiple projects at once. This scalability is not feasible with manual methods, which are resource-intensive and time-consuming.

4. Data-Driven Decision Making: By providing a comprehensive, data-driven view of worker behavior, the system enables more informed decision-making. Managers can identify patterns in worker productivity, determine causes of delays, and optimize resource allocation.

5. Cost Efficiency: While the initial development and setup of automated systems may require significant investment, the long-term savings in terms of labor costs and improved productivity can make such systems highly cost-effective. Moreover, the reduction in human error and the ability to monitor workers continuously without requiring on-site presence can significantly reduce operational costs.

Potential Applications in the Construction Industry

The potential applications of an automated system for monitoring construction worker productivity are vast. Some possible uses include:

- Performance Tracking: Tracking individual workers' productivity over time and comparing it against project benchmarks.

- Identifying Bottlenecks: Detecting delays in the workflow, such as workers waiting for materials or machinery, and providing data to address the issue.

- Safety Monitoring: Analyzing worker behavior to identify unsafe practices or conditions and sending alerts to supervisors to prevent accidents.

- Workforce Optimization: Understanding worker efficiency trends and optimizing shifts, breaks, and team compositions for better productivity.

By leveraging such a system, construction companies can not only improve productivity but also enhance worker safety, reduce delays, and increase overall project quality.

Study Objective

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This study aims to develop and evaluate an automated system for classifying construction workers' productivity behaviors using deep learning techniques. By capturing video data of worker activities and processing it with convolutional neural networks (CNNs), the system will categorize workers' behavior into specific productivity-related actions. The system's performance will be evaluated in terms of accuracy, real-time processing capability, and its potential impact on the construction industry. The ultimate goal is to create a tool that enhances productivity assessments, aids in workforce management, and improves overall construction site efficiency.

METHODS

1. Data Collection and Dataset Creation:

The dataset used for training the deep learning model was compiled by capturing video footage from multiple construction sites. The video data was annotated with labels corresponding to different productivity behaviors, including:

o Working: Engaged in productive tasks, such as operating machinery, installing materials, or assembling structures.

o Idle: Standing still or not performing tasks, likely due to lack of work or waiting for instructions.

o Waiting: Paused due to external factors such as material delivery, equipment failure, or waiting for a supervisor.

o Other: Miscellaneous behaviors such as walking between tasks, talking, or minor distractions.

The footage was captured using high-definition cameras mounted on tripods or drones for a broader perspective. A variety of construction site scenarios were included to ensure the system's ability to generalize across different types of construction activities.

2. Preprocessing and Data Augmentation:

The video frames were extracted at a rate of 30 frames per second to ensure smooth motion detection. The frames were preprocessed to standardize the input dimensions and improve the model's performance. Additionally, data augmentation techniques such as flipping, rotation, and color jittering were applied to increase the dataset's diversity and prevent overfitting.

3. Deep Learning Model Architecture:

A Convolutional Neural Network (CNN) was selected for this task due to its effectiveness in image classification tasks. The architecture was designed with several layers:

o Input Layer: The network accepts the preprocessed image frames (224x224 pixels).

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o Convolutional Layers: A series of convolutional and pooling layers were used to extract high-level features from the images.

o Fully Connected Layers: The extracted features were passed through fully connected layers to make predictions on the productivity behavior.

o Softmax Activation: The final output layer used a softmax activation function to classify the input image into one of the predefined categories: “Working,” “Idle,” “Waiting,” or “Other.”

The CNN model was trained using a labeled subset of the dataset, with an 80-20 split between training and validation sets. The Adam optimizer was used to minimize the categorical cross-entropy loss function, and training was performed over 50 epochs with a batch size of 32.

4. Evaluation Metrics:

The performance of the deep learning model was evaluated using several key metrics:

o Accuracy: The percentage of correct predictions.

o Precision and Recall: Measures of the model's ability to correctly classify each behavior category.

o F1-Score: The harmonic mean of precision and recall to balance both metrics.

o Confusion Matrix: To evaluate how well the model distinguishes between different productivity behaviors.

RESULTS

The deep learning model demonstrated promising results in classifying the productivity behavior of construction workers. The model achieved an overall accuracy of 91% on the validation set. The precision and recall for each productivity category are as follows:

- Working: Precision = 0.89, Recall = 0.92, F1-Score = 0.90
- Idle: Precision = 0.93, Recall = 0.90, F1-Score = 0.91
- Waiting: Precision = 0.85, Recall = 0.88, F1-Score = 0.86
- Other: Precision = 0.92, Recall = 0.94, F1-Score = 0.93

The model showed particular strength in classifying “Idle” and “Other” behaviors, which are often more challenging to identify due to their ambiguous nature. However, “Waiting” behaviors exhibited slightly lower precision and recall, likely due to the difficulty in distinguishing between waiting and other behaviors, such as brief pauses in work. The confusion matrix revealed minimal misclassification, with most errors occurring between “Waiting” and “Idle” categories.

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The real-time performance of the system was also evaluated. The model was able to classify the frames at a rate of 25 frames per second, allowing for live monitoring and feedback.

DISCUSSION

The results indicate that the deep learning-based automated system for classifying the productivity behavior of construction workers is highly effective in providing real-time insights into worker performance. The high accuracy and F1-scores for most categories suggest that the system can be reliably used in real-world construction environments to monitor and analyze worker productivity.

One of the strengths of the system is its ability to classify complex and subtle behaviors, such as "Idle" and "Other," which are often subjective and difficult to capture with traditional methods. The use of video data provides a more comprehensive and objective approach to productivity assessment compared to manual time studies, which can suffer from observer bias and limited coverage.

However, the model's performance in classifying "Waiting" behavior indicates that there is still room for improvement. Future work can explore incorporating additional sensor data, such as sound or environmental conditions, to better differentiate between idle and waiting states. Additionally, further training with a more diverse dataset that includes different types of construction sites and worker roles may help the system generalize better.

Another potential area for future development is the integration of this system into construction project management software. By combining the productivity data with project timelines, resource allocation, and cost estimation, the system could provide actionable insights that drive efficiency improvements, optimize workforce scheduling, and reduce project delays.

The development and implementation of an automated system for classifying the productivity behavior of construction workers using deep learning has yielded significant insights into both the potential and challenges of applying such technologies to the construction industry. The results from this study demonstrate that deep learning, specifically Convolutional Neural Networks (CNNs), can effectively and accurately classify worker behavior based on real-time video footage. However, several important aspects, including model performance, system scalability, and the broader implications for the construction industry, warrant further discussion.

Model Performance and Accuracy

One of the key highlights of this study was the high level of accuracy achieved by the deep learning model in classifying construction worker behaviors. The system demonstrated an overall classification accuracy of 91%, which is a promising result considering the complexity of real-world construction environments. The model's ability to accurately classify worker behaviors into categories such as "Working," "Idle," "Waiting," and "Other" is a significant improvement over traditional manual observation methods, which are often prone to human error and bias.

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The model achieved especially strong results in distinguishing between Idle and Working behaviors, with high precision and recall for these categories. This success can be attributed to the model's ability to learn distinctive visual patterns associated with different actions. For example, workers engaged in productive tasks often exhibit specific postures or interactions with tools and machinery, while idle workers tend to stand still or engage in non-task-related activities. The deep learning model, trained on a large and diverse dataset, was able to capture these nuanced differences, leading to its high classification accuracy.

However, the model's performance was slightly weaker when classifying "Waiting" behaviors. This can be explained by the inherent difficulty in distinguishing between waiting and other less productive behaviors, such as walking between tasks or talking with colleagues. These activities often share similar visual cues, such as short periods of inactivity, which make it harder for the model to differentiate between them. In future iterations, additional data sources such as audio input or environmental sensor data could help improve the model’s ability to detect waiting behaviors more accurately. Incorporating additional features, such as worker location or the presence of equipment and materials, may also provide more context for classifying these behaviors.

Real-Time Monitoring and Feedback

Another significant achievement of this study is the model's ability to perform real-time classification of worker behavior at a rate of 25 frames per second. This capability enables continuous monitoring of construction sites without interrupting ongoing work activities. Real-time monitoring is a critical advantage over traditional manual methods, which often require scheduled observations or periodic assessments. The automated system allows supervisors to receive immediate feedback on worker productivity, enabling them to take prompt corrective actions when needed.

For instance, if the system detects that a significant number of workers are in the Idle state, supervisors can investigate the underlying cause—whether it is a delay in material delivery, equipment malfunction, or a lack of clear instructions. Identifying such issues early in the workflow can prevent extended periods of downtime and ensure that workers remain engaged in productive tasks. Furthermore, real-time feedback enables managers to adjust resource allocation, shift patterns, or task assignments on the fly, optimizing overall workforce efficiency.

While real-time monitoring is an exciting feature, it does come with its own set of challenges. First, the system's effectiveness is highly dependent on the quality of the video footage. Poor camera placement, low-resolution video, or obstructions in the line of sight can impair the system's ability to accurately classify worker behaviors. To mitigate these issues, it is important to ensure that the cameras are strategically positioned to cover key work areas and are maintained regularly. Additionally, workers' behaviors in dynamic environments such as large construction sites may be hard to track continuously, which could result in occasional misclassifications.

Scalability and Integration into Construction Workflows

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One of the major advantages of the automated system developed in this study is its scalability. The system is capable of monitoring multiple workers across different areas of a construction site, and it can potentially be deployed on a large scale across several sites or projects. This scalability is a significant improvement over traditional methods, which are often limited in scope and require considerable human resources to monitor multiple workers simultaneously.

For example, traditional time studies or manual observations often involve a single supervisor watching a small group of workers for a limited period. This can lead to a narrow understanding of worker behavior and productivity. In contrast, the automated system can continuously monitor all workers within its field of view, providing a comprehensive and up-to-date assessment of workforce productivity. Moreover, the system can handle multiple construction sites, with real-time data being sent to a centralized dashboard for analysis and reporting.

The system can also be integrated with other construction project management tools, allowing for the analysis of worker productivity in the context of overall project timelines, resource allocation, and budget constraints. By linking productivity data with project milestones, managers can track whether delays are related to inefficiencies in worker behavior or external factors such as material shortages or equipment failures. This integrated approach provides a more holistic view of project progress and allows managers to make informed decisions about how to improve productivity and address issues in real time.

Broader Implications for the Construction Industry

The broader implications of developing an automated system for classifying construction worker productivity behavior are significant. First, the ability to accurately and efficiently monitor productivity could lead to cost savings. By identifying inefficiencies and addressing them early, construction firms can reduce labor costs associated with downtime, avoid delays, and better allocate resources. Additionally, by improving worker productivity, companies can complete projects on schedule, which translates into fewer penalties for late delivery and higher client satisfaction.

Moreover, an automated system can enhance worker safety. By continuously monitoring worker behavior, the system can detect unsafe practices, such as failure to wear protective equipment or engaging in risky activities. Early identification of such behaviors allows supervisors to intervene before accidents occur. Furthermore, tracking worker activity over time can help identify patterns of fatigue or overwork, allowing for the adjustment of work schedules to prevent injuries.

Another key benefit of this system is its potential to improve worker morale and engagement. By providing continuous feedback and identifying periods of inactivity, supervisors can take proactive steps to ensure workers remain motivated and engaged. Instead of relying on guesswork or subjective assessments, supervisors can base their decisions on objective data, ensuring a fairer and more transparent approach to performance management.

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Finally, the system's ability to analyze large datasets opens up new possibilities for data-driven decision-making in the construction industry. Over time, the system can gather valuable insights into the factors that affect worker productivity, such as the impact of weather, equipment, or management practices. These insights can help construction firms optimize their operations, improve training programs, and develop best practices for managing construction teams.

Future Directions and Limitations

While the results of this study are promising, several avenues for improvement remain. As mentioned earlier, the model's performance in classifying Waiting behavior could be enhanced by incorporating additional data sources, such as environmental sensors, equipment usage logs, or audio data. The incorporation of such multimodal data could provide a richer understanding of the context in which workers are waiting, allowing for more precise classification.

Another area for future research is the integration of the system with predictive analytics. By analyzing historical worker behavior data, the system could potentially predict periods of low productivity and recommend interventions before they occur. This proactive approach to workforce management could further optimize construction workflows and reduce project delays.

Finally, while the system is highly effective for video-based monitoring, it may not be universally applicable to all types of construction sites. For example, sites with poor camera infrastructure or those located in remote areas with limited internet access may face challenges in implementing such a system. Addressing these limitations will require innovative solutions, such as low-cost camera setups or offline processing capabilities.

CONCLUSION

This study successfully developed an automated deep learning-based system for classifying construction workers' productivity behaviors. By utilizing video footage and advanced image classification techniques, the system provides a highly accurate and efficient method for monitoring worker performance in real time. The system can be used to support decision-making processes on construction sites, identify areas for improvement, and promote more efficient project management. Further research and integration with other technologies could expand the system's capabilities and further enhance productivity monitoring in the construction industry.

REFERENCES

1. S. Kusayanagi, “A study on productivity improvement program for international construction projects,” Japanese Journal of JSCE, no. 528/VI-29, pp. 143-154, 1995.
2. Y. Gong, K. Yang, J. O. Seo, and J. G. Lee, “Wearable acceleration-based action recognition for long-term and continuous activity analysis in construction site,” Journal of Building Engineering, vol. 52, 2022.

Volume15 Issue04, April-2025, pg. 1-11

E-ISSN: 2229-3213
P-ISSN: 2229-3205
Published Date: - 01-04-2025
SJIF 2019: 4.679 2020: 5.015 2021: 5.436

3. M. Kusumoto, A. Aini, and C. Pang-Jo, "Case study of artificial intelligence at construction sites," Artificial Intelligence and Data Science, vol. 1, no. J1, pp. 301-306, Nov. 2020.
4. Takenaka Corporation, "System to track the location of elevating vehicles and workers in the construction site," Available: https://www.takenaka.co.jp/news/2016/02/01/index.html. Accessed: May 10, 2022.
5. T. Goso, A. Ochi, and S. Kusayanagi, Journal of Infrastructure Planning and Management, vol. 66, no. 1, pp. 317-328, 2010.
6. T. Goso and T. Hiromitsu, "Productivity management data collection and analysis system using ZigBee and acceleration sensors at construction sites," Monthly Automatic Recognition, vol. 8, pp. 25-30, 2015.
7. T. Goso, "Development and improvement of labor productivity assessment system in construction site by using information technology," Journal of Society for Social Management Systems, pp. SMS11-9178, 2012.
8. S. Kusayanagi and T. Goso, "Visualization in the construction management field—Visualizing the project execution process," JSCE Magazine, Civil Engineering, vol. 96, pp. 30-32, 2011
9. T. Osawa and T. Goso, "Development of an automated program for work identification at construction sites," in Proceedings of the 75th Annual Conference of the Japan Society of Civil Engineers, 2020
10. T. Osawa and T. Goso, "Construction of a productivity classification system based on a combination of pre-classification and machine learning," in Proceedings of the Symposium on Civil Engineering Informatics, Sept. 2021, vol. 46, pp. 1-4.
11. T. Goso, K. Muto, M. Hamano, T. Osawa, and R. Kasai, "Development of a system for collecting and analyzing labor environment and productivity data from construction sites using machine learning," Journal of Pavement Technology, vol. 57, no. 6, pp. 3-8, 2022.
12. N. Hashimoto and S. Takamaeda, "Investigation of approximate computation methods for machine learning-based video processing," IEICE Tech. Rep., vol. CPSY2021-59, no. DC2021-93, 2022.
13. M. H. Uddin, J. M. Kanon Ara, M. H. Rahman, and S. H. Yang, "A study of real-time physical activity recognition from motion sensors via smartphone using deep neural network," in Proc. 5th International Conference on Electrical Information and Communication Technology (EICT), 2021.
14. K. Lee and S. Han, "Convolutional neural network modeling strategy for fall-related motion recognition using acceleration features of a scaffolding structure," Automation in Construction, vol. 130, Oct. 2021.
15. R. Imai, D. Kamiya, H. Inoue, S. Tanaka, J. Sakurai, K. Sakamoto, T. Fujii, K. Mimura, and M. Ito, "Study on trial of person identification for safety management at construction sites," in Proceedings of the Symposium on Civil Engineering Informatics, 2018, vol. 43, no. 37, pp. 145-148.