DIGITAL TECHNOLOGIES FOR STEEL MANUFACTURING GRANT

Digital Computer Vision Technologies for Safety Management in Steel Manufacturing

Final Report (2022-2023)

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1.0 PROJECT SUMMARY

The active nature of the steel manufacturing plants characterized by the multifaceted assembly and interaction of humans, heavy equipment/machinery, and materials pose potential safety hazards in the work environments. As such, timely and accurate monitoring of construction activities can trigger instantaneous awareness of process-specific issues providing safety personnel and stakeholders with the information needed to make hazard control decisions easily and quickly. Although the steel industry has been developing and applying different safety management measures to prevent injuries, the implementation of digital technologies could help to enhance safety management in the workplace. Advances in digital technologies aided by computer vision have been identified as a robust approach to automatically identify and recognize unsafe behavior/conditions in active industrial work environments such as steel manufacturing plants. The main aim of the project was to investigate and implement computer vision technologies for safety management in the steel manufacturing industry. To achieve this aim, a series of activities were conducted. First, the entire work process of mini mill steel manufacturing was reviewed and studied to identify and characterize the safety and health hazards associated with each of the work processes. This inclusive process ensured there was comprehensive analysis of all activities associated with each work process to ascertain that all hazards are identified. Thereafter, the mapping of computer vision tasks with each identified hazard was done to demonstrate how computer vision can be practically applied for worker safety and health monitoring and management in the steel mini mill. Additionally, this study identified eight off-the-shelf computer vision systems and evaluated them using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a multi-criteria decision analysis method to select a candidate system based on relevant evaluation criteria. Lastly, a pilot case study was conducted to implement the candidate off-the-shelf computer vision system to ascertain their capability for safety management in steel manufacturing. The system successfully detected personal protective equipment (PPE) such as hard hats and safety gloves on workers at the steel mini mill. A set of preliminary best practices for implementing computer vision technologies for safety management in the steel manufacturing industry was proposed based on the findings of this study. It is expected that the implementation of computer vision technologies will bring about a digital transformation that can help to increase the accuracy and timeliness of decision-making for safety management in the steel manufacturing industry.

2.0 PROJECT GOALS

The effective identification and management of major safety performance indicators in steel manufacturing plants requires an integrated proactive and active management approach. The utilization of emerging digital technologies has the potential to positively impact decision-making in safety management; if data are more rapidly updated, production and safety personnel, as well as frontline workers, could take faster preventive actions to potentially correct hazardous behaviors or conditions before an injury or accident occurs. Safety management in the steel manufacturing industry has customarily relied on massive manual data collection and analysis efforts which are time-consuming, subjective, and error prone. To overcome these challenges, this proposed project study sought to investigate how computer vision can be implemented for safety management in steel manufacturing. The primary goal of the proposed project was to investigate and implement computer vision technologies for safety management in the steel manufacturing industry. The specific objectives of the proposed research project were to:

1. Characterize production processes and safety activities in steel manufacturing for computer vision applications;
2. Review computer vision technologies and applications for steel manufacturing;
3. Identify candidate off-the-shelf computer vision systems for productivity and safety management in steel manufacturing;
4. Conduct a pilot case study to implement a candidate off-the-shelf computer vision system for safety management in steel manufacturing, and;
5. Propose best practices for implementing computer vision technologies for safety management in the steel manufacturing industry.

3.0 PROJECT DETAILS

3.1 INTRODUCTION

Steel is regarded as one of the most significant materials in engineering and construction, especially in developed countries with an ever-rising demand. In 2021, the United States' overall steel demand was 98 million metric tons, surpassing the previous year's demand by approximately 15 million metric tons[1]. Steel also has a significant impact on the economic development of a nation. In 2017, the American Iron and Steel industry accounted for more than $520 billion in financial output, creating more than two million jobs[2]. These statistics emphasize the importance of steel to the economy globally. While the steel manufacturing industry has a huge impact on society, the work environment to produce steel is laden with several hazards and most literature has referred to the steelmaking site as "a high-risk work environment", which is due to how inconducive the atmosphere tends to be for the human[3, 4].

Steelmaking requires equipment of tremendous scale and power and therefore also requires extraordinary engineering and safety precautions to keep the processes running consistently and safely. Different work processes in the manufacturing operation pose several hazards associated with the work activity, including exposure of workers to extreme heat and toxic gases, high probability of workers slips, trips, or falls, fire hazards due to flammable gases and materials, the tendency of a worker being struck by a flying object, moving equipment or cranes or workers caught in confined spaces[5]. The safety programs at steelmaking companies work continuously to keep safety in the front of everyone’s minds. In addition to the safety program, steelmakers utilize engineering, training, lock-out/tag-out/try-out, and physical separation along with personal protective equipment to reduce exposure to the remaining risks[3]. Current monitoring processes to mitigate these hazards and prevent injuries indicate the need for automated detection of unsafe behavior and unsafe condition to supplement current safety management practices and reduce heavy reliance on manual inspection[6].

With the recent advances in technology and the emergence of artificial intelligence, computers' ability to serve as a reliable monitoring and detecting system has broadly expanded[7]. Manual inspection, monitoring, and detection have been predicted to be augmented by machine vision, otherwise called computer vision[8]. Manufacturers, including steelmakers, embrace new technologies as they are proven, and computer vision is one digital technology that has been developed for application to safety. Computer vision with deep learning can perform and automate tasks, ranging from object classification and detection to object tracking and action recognition[9]. When implemented in the steel manufacturing industry, these tasks could be effective for safety management in the workplace environment. Despite the efforts made by researchers to automate the monitoring of safety activities in the work environment, an automated computer vision and deep learning-based system are yet to be developed and tested for feasibility in steel manufacturing. The objective of this paper is to characterize the hazards associated with each work process in steel manufacturing, identify the applicable off-the-shelf computer vision systems for effective safety management in steel manufacturing, and propose best practices for implementing computer vision technologies for safety management in the steel manufacturing industry.

3.2 METHODOLOGY

The procedure adopted for conducting this study includes three phases as shown in Figure 1. First, the hazards in a steel mini mill manufacturing process were characterized to understand the respective potential hazards and hazard scenarios in each work process. How computer vision can be applied in such scenarios is also discussed. Second, available off-the-shelf computer vision systems that could prevent the identified potential hazard in each work process were identified. A multi-criteria decision analysis method, referred to as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), was to evaluate different systems. The off-the-shelf computer vision systems were analyzed based on the availability of certain metrics. A pilot case study was also conducted to demonstrate the efficacy of computer vision systems in the steel industry.

Figure 1: Research Process

3.2.1 Characterizing Safety Hazards for Computer Vision Applications in Steel Manufacturing

The methodology involved three stages: review, observation, and characterization. This process is illustrated in Figure 2. The review stage gave the research team an overview of the work process in a steel mini mill manufacturing process from academic literature, recent industry findings related to steel mini mill manufacturing, and online videos relating to the steel manufacturing process. With that knowledge established, the research team took a live tour of the steel mini mill to observe the work process. This combination of earlier processes enabled the research team to identify the different work processes in the steel mini mill and also identify the hazards associated with the work process. With this knowledge and experience obtained, the team was able to match them with the computer vision task, the type of data required, and the deep learning technique for analyzing the data.

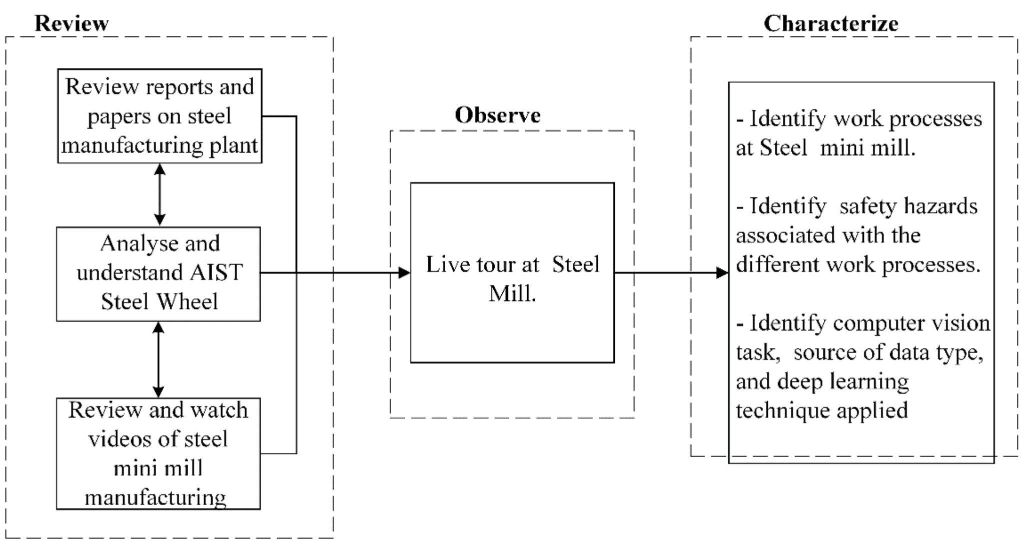

Figure 2. Safety Hazard Characterization Process

3.2.2 Evaluating Off-the-shelf Computer Vision Systems for Safety Management

For this study, selected off-the-shelf computer vision systems were evaluated. To discover these systems, an extended internet search using the Google search engine keywords such as "computer vision companies," "commercially viable object detection companies", and "Artificial intelligence for safety management" was carried out. Additionally, recommendations from industry professionals in the steel industry guided our selection. From the result, the researchers selected eight (8) currently active off-the-shelf computer vision systems that can be deployed for safety management in the steel industry. These systems were appraised on specific metrics germane to safety management in the steel manufacturing industry. Some of these metrics include PPE detection, the system's ability to detect slips, trips, and falls, the system's data privacy, the system's ability to detect the proximity of humans to heavy equipment, ease of use of the Graphical User Interface (GUI), the systems current application in the steel industry, and the ability of the system to detect in real-time. TOPSIS was utilized to select the off-the-shelf system out of the eight initially proposed systems. The TOPSIS model is a multi-criteria decision-making (MCDM) model first introduced by Hwang and Yoon in 1981 to rank alternatives with a finite number of criteria, selecting the alternative closest to the ideal solution44. The flow process is depicted in Figure 3.

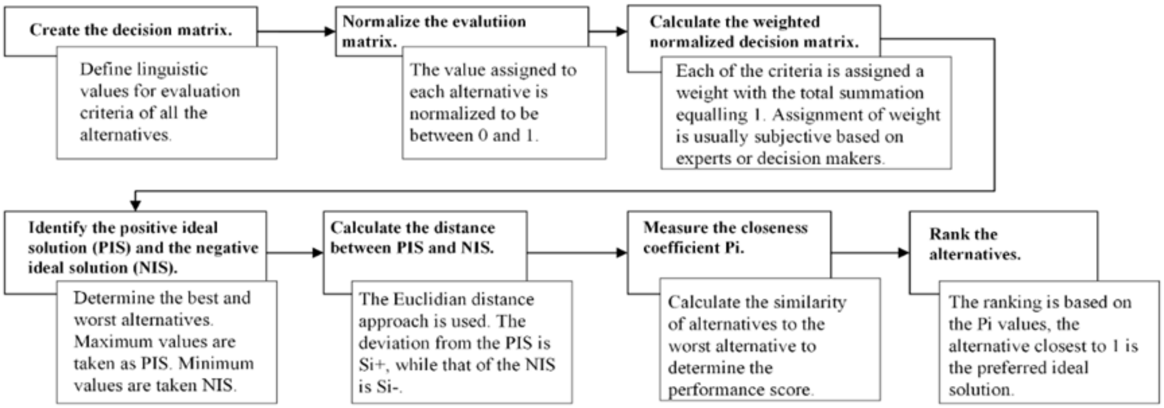

Figure 3. TOPSIS Process for Evaluating Off-the-shelf Computer Vision Systems

3.2.3 Case Study Procedure

The case study aimed to classify and detect PPE (hard hats and safety gloves) on workers in the steel manufacturing work environment. Video data was retrieved from installed closed-circuit television cameras (CCTV) in a steel manufacturing site, the computer vision system was developed using CNN based object detection model to classify workers with or without hard hats, and also workers with or without hand gloves. The data obtained from the CCTV at the steel mill included only a few scenarios in which workers were without hard hats. However, for effective training of the model to give a better performance, it was essential to have a balanced dataset that should include infringements, which in this case would be workers without hard hats. So, it was imperative to resolve this problem during the data preprocessing phase using stable diffusion inpainting45. Figure 4 shows the result of the method. Figure 4(a) shows the original data, while Figure 4(b) shows the data after synthesizing.

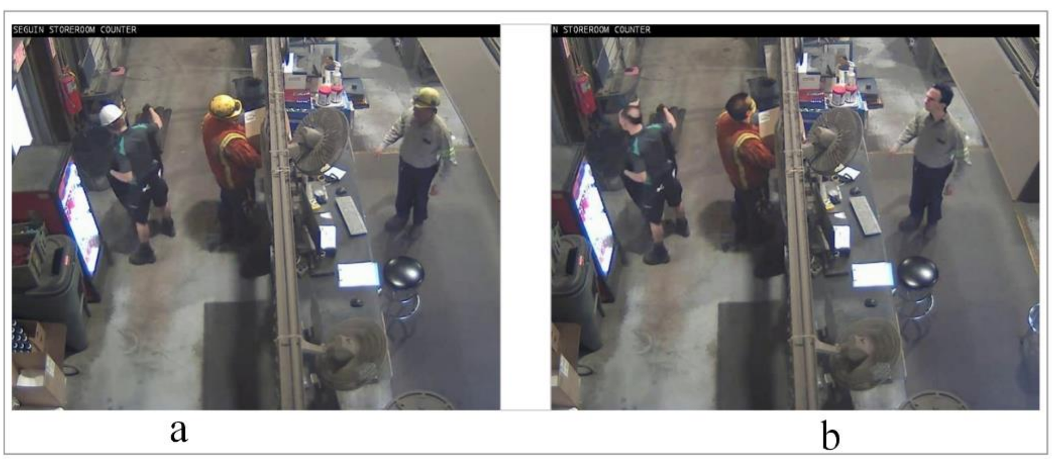

Figure 4. Data Augmentation using Stable Diffusion Inpainting Technique (a) Original Data (b) Synthesized Data

3.3 RESULTS AND DISCUSSION

3.3.1 Characterization of Computer Vision Applications for Safety Management in Steel Manufacturing

For proper safety management at the mini mill, there is a need to analyze the hazards in each work process involved explicitly. In order to characterize the hazards, the research team conducted a tour of a steel mill, reviewed reports of steel manufacturing plants that use the mill steelmaking process, studied the AIST Steel Wheel, and watched different videos of the mill steelmaking process. The research team conducted a comprehensive appraisal of the hazards to categorize them based on how they can be detected, tracked, or monitored to protect workers and prevent injuries, illnesses, and fatalities.

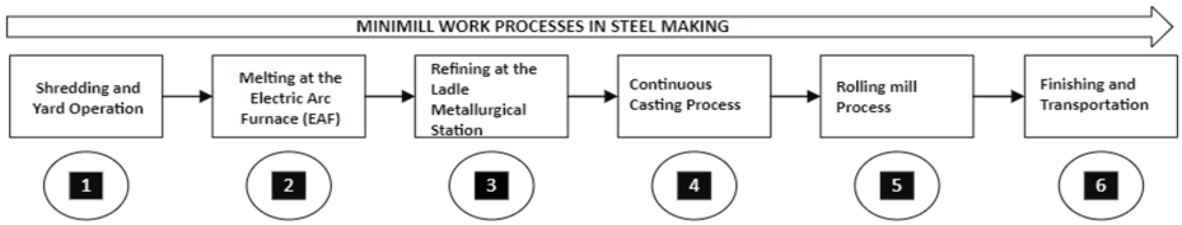

Figure 5. Mini Mills Work Process

For mini mills that have a shredder on-site, the work process begins with the shredding and yard operations and proceeds to the melting of scrap metal at the electric arc furnace, the refining station at the ladle metallurgical station (LMS), continuous casting, rolling mill, and the finishing and transportation process as shown in Figure 5. The process starts with the shredder, where the scrap metals are crushed and there is a separation between the ferrous and non-ferrous metal. The ferrous scrap is charged and melted in the electric arc furnace, after which the molten steel is tapped and often further refined and purified in the LMS. The molten steel is formed into semi-finished products such as billets, blooms, or slabs in the continuous caster. These semi-finished products are further processed in the rolling mill into finished products using methods such as annealing, hot forming, cold rolling, pickling, galvanizing, coating, or painting. The process ends with the finishing & transportation stage in which the products are cooled, sheared, bent, or straightened as required and then transported to the site or fabrication shop. shows this process. These hazards in the entire work process were critically analyzed, specific hazards associated with each work process were highlighted, and how computer vision tasks can help detect the identified hazard before it leads to an incident. Table 2. shows the characterization of the hazards; the model is adjustable and can fit into other steelmaking processes.

Table 2: Safety Hazard Characterization for Computer Vision Applications in Steel Manufacturing

Safety Hazard	Computer Vision Task	Data Collection Device	Sample Scenarios	Computer Vision Application	Source
Struck-by	Object tracking, Object detection	RGB Cameras, RGBD Cameras, Stereo Vision Cameras	**Shredder & Yard Operation (1)**: In mini mills with a shredder, workers are exposed to flying objects as raw materials are shredded and crushed. **Melting at Electric Arc Furnace (EAF) (2):** Moving equipment such as dump trucks or gantry cranes can strike workers. **Finishing and Transportation (6):** Workers can be struck by finished products, shears and bends rebars, and by the trucks used for loading.	CV in real-time can track personnel and alert when workers are in proximity to the danger of being struck by.	46
Caught in-between	Object tracking, Object detection	RGB Cameras, RGBD Cameras, Stereo Vision Cameras	**Shredder & Yard Operation (1)**: In mini mills with a shredder, workers are exposed to the danger of being caught in between equipment, shredder mill, and raw materials at the shredding yard. **Melting at Electric Arc Furnace (EAF) (2):** There is a danger of workers caught between load transferred from crane (within swing radius) and stationary or moving objects in the steel shop. **Finishing and Transportation (6):** Similarly, during the finishing and transportation, there is a hazard of workers being caught-between trucks and objects, which could be the stacked rebars.	CV task can help in classifying, detecting, and tracking people and equipment, therefore alerting when workers are in proximity to these hazardous scenarios.	6, 47

Safety Hazard	Computer Vision Task	Data Collection Device	Sample Scenarios	Computer Vision Application	Source
Fire	Object detection, Object classification	RGB Cameras, RGBD Cameras, Infrared Cameras, Flash LIDAR	**Melting at the EAF (2):** Fire hazard is very high at the furnace. Molten steel is very usually at very high temperatures>2800F. This increases the occurrence of fire hazards. **Refining at the LMS (3):** LMS is a hotspot that includes molten steel undergoing its purification process, alloying, desulphurization, degassing, etc. **Casting Process (4):** Solidification of liquid steel involves working at high temperatures, and there is a possibility of a fire hazard in this work process.	CV technologies can successfully detect fire at its incipient stage. Most of the time, earlier than smoke detectors due to its early detection, using DL programs.	48
Spills	Object classification, segmentation and detection	RGB Camera, RGBD Cameras	**Melting at the Electric Arc Furnace (EAF) (2):** Spills from the molten metal at the furnace can pose a hazard to workers. **Refining at the LMS (3):** Spill hazard is also prominent during the tapping process from EAF to the refining station. **Casting Process (4):** There is the likelihood of spills of molten steel, especially during the transfer of molten steel from the Ladle to the tundish.	CV using segmentation task can detect these spills and alert workers in real-time when in proximity to the spills.	28
Slips/Trips/ Falls	Object detection, Action recognition	RGB Cameras, RGBD Cameras	**Melting at the EAF (2):** Slips trips and Falls occurrence is high at the furnace due to the nature of activities during this process. There is usually reduced visibility at this location due to the excess heat from the furnace, which increases the possibility of trips and falls. **Rolling Mill (5):** Workers may trip in the rolling mill due to improperly stacked rolling equipment. **Finishing and Transportation (6):** Workers are exposed to the danger of slips, trips, and fall during the finishing and transportation work process; stacked rebars can cause this too.	CV can detect workers' proximity to the hazards, causing slips, trips, and falls, and also detect when workers fall; this is viable in real-time when integrated with sensors that can be integrated into safety vests, smart watches, or hard hats.	49, 50
Bad worker posture	Pose estimation / Action recognition	RGB Cameras, RGBD Cameras, Stereo Vision Cameras	This hazard is recognized and characterized in all phases of the work process. Bad worker posture is observed in all work areas that involve workers' presence. There is an increasing need to observe human interaction with tools, equipment, and the environment.	CV techniques using images and videos can detect workers' postures in every work process and send alerts when workers' posture poses a risk to their safety.	37
No PPE	Classification, Object detection	RGB Cameras, RGBD Cameras	Personal Protective Equipment (PPE) is required at all work processes in the mini mill. These protective gears are to be worn at all work process locations.	CV using images can detect workers not wearing their PPE's, including safety helmets, vests, gloves, and in some cases, glasses.	20, 9
Extreme temperature	Image classification, Segmentation, Object detection	Infrared Cameras (IR)	The entire work process in the mini mill steel process subjects and endangers workers to extremely high temperatures, which needs to be critically monitored.	CV using heat maps on face detection of workers can detect based on varying color codes when workers are experiencing heat stress.	51

3.3.2 Evaluation of Off-the-shelf Computer Vision Systems for Safety Management

TOPSIS multi-criteria model was used to evaluate the off-the-shelf computer vision systems to select the best alternative closest to the ideal solution. The TOPSIS flow chart process was described in Figure 3.

Tables 3 to 6 show the TOPSIS model analysis as described in the research methodology. Table 3 shows the evaluation criteria with their assigned linguistic values, the values were measured using availability, “2” signifies available, and “1” signifies not available. Table 4 shows the elements of the evaluation matrix, each of the evaluation criteria has been assigned a linguistic value for each of the computer vision systems. Also, the weight of each criterion is distributed, to sum up to 1. Table 5 shows the normalized values of the evaluation matrix.

Table 3: Definition of Linguistic Values for Evaluation Criteria

Linguistic Value	PPED	DP	OA	EG	H	GF	PHE	STF	AS	RT	GUI
Available = 2	2	2	2	2	2	2	2	2	2	2	2
Not Available = 1	1	1	1	1	1	1	1	1	1	1	1

PPED = PPE Detection, DP = Data Privacy, OA = Other Application, EG = Ergonomics, H = Health, GF =Geofencing, PHE = Proximity to Heavy Equipment, STF = Slips, Trips, and Falls, AS = Application in Steel Manufacturing, RT = Real Time, GUI = User-friendliness of Graphical User Interface.

Table 4: Elements of the Evaluation Matrix

CV System	PPED	DP	OA	EG	H	GF	PHE	STF	AS	RT	GUI
Everguard	2	2	1	2	2	2	2	2	2	2	2
Intense eye	2	2	1	2	1	1	2	2	1	2	2
Cogniac	2	2	2	1	1	1	1	1	1	2	2
Protex	2	2	1	1	1	1	1	1	1	2	2
Rhyton	2	1	1	2	1	1	2	1	1	1	1
Chooch	2	2	2	1	1	2	2	1	1	2	2
Kogniz	2	1	2	1	1	1	2	2	1	2	2
Matroid	2	2	2	1	1	2	1	1	1	2	2
Weights	0.1	0.05	0.1	0.1	0.05	0.1	0.1	0.1	0.15	0.1	0.05

Table 5. Normalized Values of the Evaluation Matrix

CV System	PPED	DP	OA	EG	H	GF	PHE	STF	AS	RT	GUI
Everguard	0.354	0.392	0.224	0.485	0.603	0.485	0.417	0.485	0.603	0.371	0.371
Intense eye	0.354	0.392	0.224	0.485	0.302	0.243	0.417	0.485	0.302	0.371	0.371
Cogniac	0.354	0.392	0.447	0.243	0.302	0.243	0.209	0.243	0.302	0.371	0.371
Protex	0.354	0.392	0.224	0.243	0.302	0.243	0.209	0.243	0.302	0.371	0.371
Rhyton	0.354	0.196	0.224	0.485	0.302	0.243	0.417	0.243	0.302	0.186	0.186
Chooch	0.354	0.392	0.447	0.243	0.302	0.485	0.417	0.243	0.302	0.371	0.371
Kogniz	0.354	0.196	0.447	0.243	0.302	0.243	0.417	0.485	0.302	0.371	0.371
Matroid	0.354	0.392	0.447	0.243	0.302	0.485	0.209	0.243	0.302	0.371	0.371

Table 6 shows the weighted values of the evaluation matrix and the rankings of the alternatives. From the P-value, which is the performance score of the alternatives, the CV systems' rankings in descending order are Everguard, Intense eye, Chooch, Kogniz, Matroid, Cogniac, Rhyton, and Protex. The values of the top three alternatives obtained for their relative closeness to the ideal solution are 0.760, 0.444, and 0.435, respectively. The outcome of this multi-criteria decision-making (MCDM) process identifies the Everguard computer vision system as the best off-the-shelf computer vision system among the appraised systems that can be used for safety management in steel manufacturing.

Table 6: Weighted Values of Evaluation Matrix and Ranking of Alternatives

CV System	PPED	DP	OA	EG	H	GF	PHE	STF	AS	RT	GUI	S+	S-	Pi
Everguard	0.035	0.020	0.022	0.049	0.030	0.049	0.042	0.049	0.090	0.037	0.019	0.022	0.071	0.760
Intense eye	0.035	0.020	0.022	0.049	0.015	0.024	0.042	0.049	0.045	0.037	0.019	0.058	0.046	0.444
Cogniac	0.035	0.020	0.045	0.024	0.015	0.024	0.021	0.024	0.045	0.037	0.019	0.067	0.032	0.324
Protex	0.035	0.020	0.022	0.024	0.015	0.024	0.021	0.024	0.045	0.037	0.019	0.071	0.023	0.246
Rhyton	0.035	0.010	0.022	0.049	0.015	0.024	0.042	0.024	0.045	0.019	0.009	0.067	0.032	0.323
Chooch	0.035	0.020	0.045	0.024	0.015	0.049	0.042	0.024	0.045	0.037	0.019	0.059	0.045	0.435
Kogniz	0.035	0.010	0.045	0.024	0.015	0.024	0.042	0.049	0.045	0.037	0.019	0.060	0.044	0.426
Matroid	0.035	0.020	0.045	0.024	0.015	0.049	0.021	0.024	0.045	0.037	0.019	0.062	0.040	0.392
V+	0.035	0.020	0.045	0.049	0.030	0.049	0.042	0.049	0.090	0.037	0.019	0.035	0.020	0.045
V-	0.035	0.010	0.022	0.024	0.015	0.024	0.021	0.024	0.045	0.019	0.009	0.035	0.010	0.022

3.3.3 Case Study Results

At this initial implementation, the pilot study conducted by Everguard successfully detected workers with PPE and those without PPE. The PPE detection tested for were hard hats and hand gloves. The results gave a decent performance for the computer vision model. Figure 6. gives a snapshot of the detection model during implementation.

a) Bounding box color-coded in red showing a worker not wearing hard hats

b) Image shows incorrect inference results, the model could not detect the hard hats on workers

c) A zoomed-in image showing two workers; one wearing protective gloves and the other not. The different color-codes highlight this

Figure 6. PPE Detection

For the hard hat detection as seen in Figure 6(a), the blue bounding box shows a true positive detection of hard hats, while the red bounding box shows an instance where a worker is without his hard hat. This CV system uses the tracking-by-detection task to track the workers' movement frame by frame on the video and is able to detect the PPE infraction. Although the model could detect the PPE on workers most of the time, some limitations were faced, which affected the model's accuracy in giving correct inference results. Firstly, the videos were in grayscale, especially those captured at the manufacturing plant store. Secondly, in scenarios in which the workers were far from the camera. This is observed in Figure 6(b).

3.4 PRELIMINARY BEST PRACTICES FOR IMPLEMENTING COMPUTER VISION TECHNOLOGIES

3.4.1 Define and Establish the Goal and Objectives

This involves understanding, defining, and analyzing the hazards and incidents associated with the steel manufacturing mill and establishing the targeted goal and objectives to mitigate or remove the hazards and prevent potential incidents. To get the most for the implementation of the new technology system, the identified goals and objectives must be SMART (specific, measurable, attainable, results-oriented, and time-bound) and be in alignment with the organization's business metrics.

3.4.2 Communicate with Stakeholders and Obtain Employee Buy-in

The reason for the proposed implementation of the technology system must be effectively communicated to all the stakeholders including both the management and non-management employees (i.e., frontline workers). This would involve a detailed plan for implementation, testing, training, actual implementation, and operation support. It should be noted and well-understood that not all participants will need to hear the same message at the same time in the same way. The benefits and impact of the technology system on worker safety performance should be clearly communicated to increase workers' buy-in.

3.4.3 Identify and Assign Champions

To facilitate the deployment of the technology system, a change management plan must be put in place. As part of the plan, having champions will significantly enhance the success of the implementation. These champions with extensive knowledge about the new technology system engage and interact with users at all levels of the organization. They will communicate and engage with their peers in a way that outside consultants cannot, increasing the implementation success.

3.4.4 Select Computer Vision System

Based on the findings of this study, a methodology for evaluating and selecting computer vision systems was presented. For instance, the technique for order of preference by similarity to ideal solutions (TOPSIS) process demonstrated in this study for the evaluation and selection of off-the-shelf computer vision systems can be used. The use of this multi-criteria decision-making process is expected to support stakeholders in making decisions on systems to implement for workers' safety and health monitoring in steel manufacturing.

3.4.5 Educate and Train Employees

Adequate resources and time should be dedicated to educating and training employees in the new technology system. Various training methods including electronic, classroom, and hands-on to reach every type of learner, increase training effectiveness, and enhance the implementation of the new technology system. Employees should be instructed about the value of the new technology system, functionality, and required maintenance. The champions should create and organize the training materials, as well as conduct the training for the employees. After all the employees have received the required training, the systems should be deployed in initial field trials before full implementation.

3.4.6 Monitor and Measure

Upon implementation of the technology system, a monitoring and measurement procedure should be put in place to fully understand its effectiveness and the need for improvements. Offering opportunities for feedback to make everyone feel part of the change and gain valuable insights into what is working well and what may need to be revised. These practices have the potential to help drive engagement, enhance organizational efficiencies, and maximize return on investment.

3.5 CONCLUSIONS

As the steel manufacturing industry increases its production rate to meet the increasing demand for steel today, safety management in the steel industry is exigent. Computer vision tasks such as object detection, classification, segmentation, and action recognition have great potential to be used in safety management applications to mitigate hazards encountered in steel manufacturing plants, thereby protecting workers' lives and heavy investments in properties, equipment, and the environment. This paper characterized the hazards in the entire work process of mini mill steel manufacturing, thereby highlighting the significant hazards associated with each of the work processes. The holistic process ensured there was an extensive dissection of all activities associated with each work process, ensuring every hazard is identified. Also, the study matched computer vision tasks to each identified hazard, demonstrating how computer vision technology can be applied practically in actively monitoring and managing a worksite against hazards. Additionally, this study identified eight commercially available computer vision systems and evaluated them using the TOPSIS model to select the most viable based on the evaluation criteria. The model ranked Everguard systems as the best system from the evaluated systems that can be deployed in steel manufacturing mills to effectively manage worker safety. Lastly, a pilot case study was carried out to ascertain the capability of the CV system. The system successfully detected PPE (hard hats and safety gloves) on steelworkers at the manufacturing plant.

The outcome of this study would enable stakeholders in the steel manufacturing industry to improve their decision-making in safety management and develop a robust comprehension of how to harness computer vision technology in each work process of the mini mill steel manufacturing plant. This characterization is adaptable and can be modified to be applied in the integrated mill steel manufacturing process. Research is ongoing to conduct a pilot case study on the pose estimation and ergonomics of workers in the steel manufacturing site. Future work can look at computer vision and its application towards productivity in the steel industry. Additionally, future studies can focus on understanding stakeholders' perception of steel manufacturing companies towards being apprehensive of computer vision technologies, especially with data privacy and retention.

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4.0 DISSEMINATION OF RESULTS

This final report containing the findings of the research study including the research activities, results, and conclusions, along with recommendations for further studies and implementation in practice, is being submitted to the Association for Iron & Steel Technology (AIST) Foundation for dissemination. A peer-reviewed conference paper that describes the research study has been published in the proceedings and presented at AISTech 2023, The Iron & Steel Technology Conference and Exposition, May 8 – 11, 2023, Huntington Place Convention Center, Detroit, MI. In addition, a research poster was also presented at AISTech 2023. The research study will also be published in Safety First, a publication of the Association for Iron & Steel Technology, and potentially another journal outlet to further increase the visibility of the work. All these will be used to disseminate the results of the project to students, industry professionals, and researchers in the iron and steel industry. This will help provide new or alternative solutions that deepen the understanding of the technical issues involved in digitizing the steel industry and widespread applicability to the steel industry and probability of success. In addition, at least a seminar presentation will be hosted at The University of Texas at San Antonio to further disseminate the results of the project to students in various disciplines including Construction Science & Management, Civil Engineering, Mechanical, and Materials Engineering at the university. These seminars will be anchored by the students that participated in this project to share the results of this project, as well as AIST student programs to increase direct steel industry engagement with students interested in digital technology and tools. The findings of the research will also be integrated into the curriculum of the Construction Safety course taught by the Principal Investigator (PI) at The University of Texas at San Antonio.

5.0 PROJECT SCHEDULE

The project was conducted during the 2022 – 2023 academic year starting from October 2022 to May 2023. The list of main tasks/milestones and their respective approximate timelines/durations are shown below.

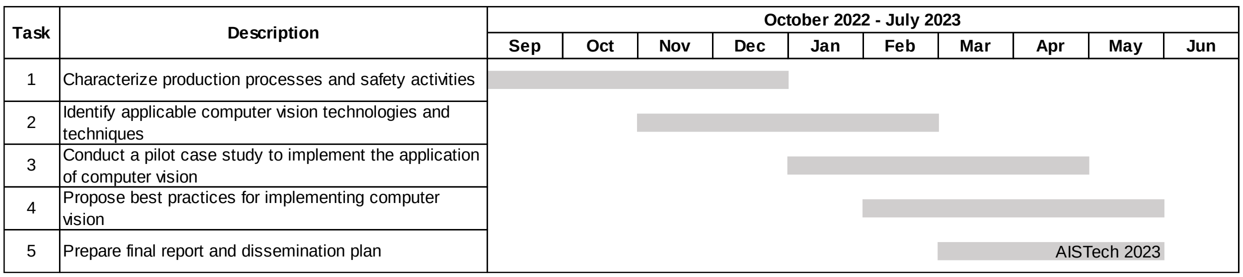

Figure 4: Project Schedule

6.0 PROJECT COST

The project cost for this research study was $30,000 for one academic calendar year and was expended on salaries for the PI, Co-PI, and the Graduate Research Assistant (GRA) that worked on the project, purchase of materials and supplies used for the study, as well as conference registrations, and domestic travels to AISTech 2023 to present the findings of the project.

7.0 STUDENT PARTICIPATION

In addition to Roy Lan, the Civil Engineering graduate student from The University of Texas at San Antonio that worked directly with Drs. Awolusi and Cai to conduct the research study, two other Civil Engineering graduate students (Chinedu Okonkwo and Xiaoyun Liang) and two Construction Science and Management undergraduate students (Katelyn Trevino and Stefanie Zuniga) from The University of Texas at San Antonio participated in the steel mill tour conducted at the beginning of the project, the presentation from a vendor on a computer vision system, and learned from this project. Roy Lan co-presented the project findings with the research team leader and in addition presented a research poster to fellow students, industry professionals, and researchers at AISTech 2023. All these students involved in the project will be playing key roles in the continuous dissemination of the findings of the research. At least a seminar will be hosted at The University of Texas at San Antonio to disseminate the results of the project to students in various disciplines at the university to share the findings of the project, as well as AIST student programs to increase direct steel industry engagement with students interested in digital technology and tools. Although the PI does not have information about the number of students from the university who have accepted employment in the steel industry, it is expected that the dissemination of the results of this project within the university will foster awareness about steel manufacturing, thereby potentially increasing the number of students that will accept employment in the steel industry upon graduation.

8.0 STEEL PLANT INTERACTION

As part of this project, the research team consisting of the research team leader (PI), Co-PI, and students had a tour of the steel mill at the beginning of the project to acquire first-hand knowledge about the entire steel manufacturing process, learn about the hazards that workers in steel manufacturing mills are exposed to, and safety management practices adopted to protect workers. The steel mill tour provided a unique experience for the students in the sense that it exposed them to exciting activities in the different areas of the steel manufacturing process. This plant tour was the third organized through the partnership of Dr. Awolusi with the steel plant indicating that a strong relationship that creates avenues and opportunities for the continuous exposure of students from The University of Texas at San Antonio to the steel manufacturing process already exists. More steel plant tours will be conducted either as part of future research projects or class field trips for experiential learning. After the steel tour conducted as part of this project, the research team had a kick-off meeting with the industry mentors, Dr. Sam Matson, and. Mike Volkmann from CMC Steel Texas to discuss the project and recommendations on the scope, goal, and objectives of the project based on the needs of the steel manufacturing industry. The students interacted with the industry mentors, asked questions, and overall found the meeting very productive and highly enlightening. The graduated student that worked directly on the project was involved in all the meetings and interactions to took place throughout the project with the steel industry mentors and digital computer technologies vendor.

9.0 PROJECT DURATION

The project was conducted during the 2022 – 2023 academic year starting from October 2022 to May 2023.

10.0 FUTURE OF GRANT

☒ The plans contained in the original proposal are now complete. I have $1,393.41 remaining and request permission to continue promoting the steel industry to engineering students at my university using these funds. I agree to provide an annual report to AIST until the funds are depleted.

☒ The plans contained in the original proposal are now complete. I would like to discuss how the final results could be posted to the website, shared with other universities, shared with AIST members, added to the AIST Library, or presented at a conference.

06-15-2023

Signature of Professor and Date