As technology evolves and society changes, accounting and auditing students must develop diverse skills, including technical proficiency and critical thinking. Environmental, Social, and Governance (ESG) concerns are increasingly important, driving nations and corporations to take action. Investors prioritize ESG criteria, while consumers prefer eco-friendly products and services. Preventing Greenwashing is important for future auditors. This teaching case highlights the role of accountants in managing E-waste under the Environmental pillar of ESG. Students explore new technologies like Computer Assisted Audit Techniques (CAATs) through hands-on exercises to address these challenges.

**KEYWORDS**
ESG, Obsolescence Management, CAATs, Machine Learning, Greenwashing, E-waste.

1 | INTRODUCTION

Environmental, Social, and Governance (ESG) issues have evolved into vital considerations across daily life, business operations, and investments (Al Amosh & Khatib, 2023). Initially coined in the report “Who Cares Wins” by the United Nations Global Compact Initiative (UN, 2004), ESG amalgamates three ethical pillars—environmental, social, and governance, delineating specific assessment targets (Billio et al., 2021). The global landscape, marked by extreme weather, financial crises, and the recent COVID-19 pandemic, has transformed sustainability from a luxury into a necessity (Adams & Abhayawansa, 2022). Stakeholders and investors now demand transparency regarding sustainability practices (Fernando, 2021). Customers seek shared values in their purchase decisions, while partners and suppliers prioritize demonstrable ESG initiatives (Santos et al., 2023). Hence, sustainability and ESG have gained unparalleled significance.

In 2015, the United Nations’ commitment to 17 Sustainable Development Goals (SDGs) by 2030 (United Nations, 2023) where waste management could help in pollution, climate change, or poverty (Rodić & Wilson, 2017). However, technological advancements contributing to enhanced living standards also generate Waste Electrical and Electronic Equipment (WEEE) or E-waste, significantly impacting SDGs (Guarnieri et al., 2022; Shittu et al., 2020). Of particular concern within WEEE is obsolescence and redundancy (Shittu et al., 2020), which can be managed through reactive or proactive measures (Rust et al., 2022).

Artificial Intelligence (AI) innovation has revolutionized modern capabilities, potentially affecting 18 percent of global jobs, about 300 million jobs, including accounting professions (Johnson, 2023; Frey & Osborne, 2017; Leitner-Hanetseder et al., 2021). However, there’s a transformative view that AI will augment rather than replace professional tasks (Leitner-Hanetseder et al., 2021; Moll & Yigitbasioglu, 2019; Oesterreich et al., 2019).

Despite these advancements, accounting education has historically centered around textbooks and lectures, promoting an emphasis on completing tasks with standardized solutions (Rajeevan, 2020). This approach, however, clashes with the tech-savvy nature of the current student generation, leading to decreased interest and patience (Behn et al., 2012; Rajeevan, 2020). Recognizing this discrepancy, there’s a growing demand for the evolution of accounting education (Gittings et al., 2020), which has already begun manifesting (Apostolou et al., 2019). Undoubtedly, it is the utmost aim of business education to make students become critical thinkers and problem solvers (Rajeevan, 2020) in modern dynamic business environment. Prior pedagogical research underlines the efficacy of experiential learning with real-world contexts in fostering robust student learning (Gittings et al., 2020; Wang et al., 2022).

In response to the escalating significance of ESG and the challenges posed by emerging technologies, this teaching case aims to provide a hands-on exercise. It is designed to instruct students and practitioners on proactive E-waste management within daily business operations, employing AI-based technology as part of experiential learning. This initiative is crucial considering the prevalent reactive approach adopted by most individuals towards E-waste management.

Moreover, in our swiftly evolving era, conventional school learning may not adequately equip individuals to tackle the myriad new issues that arise. This teaching case seeks to prompt readers to upskill themselves with new technology and hone critical thinking abilities. By doing so, they can effectively address questions or challenges encountered in their daily lives.
2 | LITERATURE REVIEW

E-waste

E-waste comprises discarded electronic and electrical equipment, spanning a diverse range of items like telecommunications devices, IT equipment, household electronics, lighting tools, and more (Chen et al., 2015; Shahabuddin et al., 2023). Its emergence is attributed to technological evolution, regulatory changes, market demand, among other factors (Shittu et al., 2021; Trabelsi et al., 2021), contributing to its annual escalation mainly due to shorter electronic product life cycles (Bunduchi & Candi, 2022). In 2019, E-waste generation reached 53.6 million tons, projected to soar to 74.7 million tons by 2030 (Forti et al., 2020). Alarming is the improper handling of E-waste; in 2019, around 83 percent (53.6 million tons) lacked proper documentation, posing severe health and environmental threats, especially when containing toxic materials like mercury and lead (Ruiz, 2022). This exponential growth in E-waste generation has raised concerns about e-waste management or obsolescence management (Shittu et al., 2021).

Obsolescence management

Obsolescence, while not a new issue, remains an inevitable challenge but can be mitigated through proactive planning (Trabelsi et al., 2021). Sandborn (2013) outlines three distinct approaches to obsolescence management:

1. **Reactive Management:** Addressing obsolescence issues after they occur.
2. **Proactive Management:** Taking preventive measures before obsolescence arises.
3. **Strategic Management:** Combining mitigation methods and design updates.

The choice between these approaches often leans toward proactive management, particularly when the costs are higher, given that obsolescence management aims to minimize costs and the negative impacts of resulting E-waste throughout a product’s life cycle—from design to production and maintenance (Trabelsi et al., 2021).

Notably, obsolescence prediction serves as a pivotal aspect of proactive management (Sandborn et al., 2011). Numerous researchers have explored predictive methods, often relying on mathematical approaches. With the rapid advancements in computer science, machine learning-based techniques offer a more accessible and precise means to anticipate obsolescence (Jennings et al., 2016; Trabelsi et al., 2021).

Machine learning

Machine learning, a subset of AI, primarily focuses on training algorithms to generate optimized models for tasks like data sorting, forecasting, and comprehensive data analysis (Mirjalili et al., 2020). This field has attracted substantial investments from leading companies, reshaping various industries such as manufacturing, retail, banking, and more (Mirjalili et al., 2020). Notably, machine learning has facilitated efficiency improvements within these sectors, with legacy companies leveraging this technology to streamline operations (MIT & Brown, 2021).

In the domain of auditing, AI adoption has been reported, particularly in handling repetitive audit tasks and conducting internal control testing (Qasim & Kharbat, 2020). In management accounting, specific facets of AI, such as machine learning, hold relevance, aiding in revenue forecasting, transaction classification, accounting estimations, and even obsolescence prediction through historical transaction analysis (Ding et al., 2020; Jennings et al., 2016; Qasim &
However, despite its potential benefits, a gap exists between the anticipated need for new skills and the current capabilities of the workforce. The 2023 Work Trend Index by Microsoft, surveying 31,000 individuals across 31 countries, reveals that while 85 percent of leaders foresee the necessity for new skills, 71 percent of respondents admit lacking these required capabilities (Microsoft stories., 2023). Consequently, there’s a growing suggestion that people should work collaboratively with AI (Crouse, 2023). For accounting graduates and practitioners, leveraging information technology and machine learning could address disparities in professional resources, offering a pathway to bridge the current and future skill gaps (Qasim & Kharbat, 2020).

The expectation-performance gap in accounting education

The landscape of accounting as a profession has witnessed an intensifying demand for talent to retain its pivotal role in society amidst technological evolution and socio-economic advancements (Barth, 2018; Berry & Routon, 2020). Consequently, there has been a growing consensus advocating for a holistic approach in modern accounting education. This approach emphasizes the incorporation of a blend of soft and hard skills alongside theoretical knowledge (Berry & Routon, 2020). Communication, critical thinking, problem-solving, computer application, and AI are among the pivotal skills consistently advocated by both academia and practitioners. These competencies are deemed essential for accounting graduates to bridge the expectation-performance gap in accounting education (Berry & Routon, 2020; Bw online bureau., 2023; Dolce, 2020; Mhlongo, 2020; Qasim & Kharbat, 2020).

However, criticisms have been directed at traditional accounting education methodologies that primarily focus on task completion, rote memorization, and providing definitive answers. These pedagogical approaches, centered on professional accreditation rather than practical application, have drawn scrutiny (O’Connell et al., 2015; Hassall & Joyce, 2014; Turner & Baskerville, 2013).

In response to these criticisms, there has been a notable upsurge of interest in experiential learning within accounting education. This pedagogical approach aims to generate knowledge through immersive experiences within real-world contexts (Hassall & Joyce, 2014; Kolb, 2014). Consequently, many universities have initiated the integration of more experiential learning courses or activities into their accounting curricula (Gittings et al., 2020).

Experiential learning

Experiential learning, rooted in the principle of experiencing to understand, contrasts with traditional methods of teaching by emphasizing hands-on involvement and active participation (Adom et al., 2016; Dogru & Kalender, 2007; Honebein, 1996). As Confucius famously articulated, “I hear and I forget. I see and I remember. I do and I understand,” encapsulating the essence of experiential learning (Adom et al., 2016; Hassall & Joyce, 2014).

Extensive research underscores the manifold advantages of experiential learning. This pedagogical approach enables students to amalgamate context with their experiences, fostering the enhancement of critical problem-solving skills and augmenting their productivity as future professionals (Butler et al., 2019; Wang, 2022). For accounting students, typically devoid of real-world business exposure, this approach becomes instrumental in comprehending intricate concepts like business processes, internal controls, and data flows (Wang, 2022).

Based on the synthesized literature, our design involves an experiential learning case grounded in real-world operational scenarios encompassing obsolescence management and machine learning. This approach intends to fortify...
students’ soft skills such as communication, critical thinking, and problem-solving, alongside honing their technical prowess in utilizing relevant tools. Furthermore, instructors or teachers, if present, can expand upon these scenarios to ensure students meet the intended learning objectives effectively.

3 | BACKGROUND INFORMATION OF THE COMPANY

About Paragon

Paragon Heatsinks Corporation, hereafter referred to as “Paragon,” operates globally with production facilities in the United States and Asia. Established in the 1970s, Paragon specializes in the design and manufacturing of custom heatsinks tailored for the advanced microelectronics and components industries worldwide. Its niche market includes cell sites, industrial computers, medical equipment, and similar sectors.

Paragon’s success lies in its concurrent engineering prowess. The company’s sales team, comprising sales professionals, engineers, and designers, collaborates closely with clients right from the inception of product development. This collaborative approach has resulted in strong client relationships and consistently high-quality products that meet client expectations. Ensuring high client satisfaction remains pivotal for Paragon. This requires the company to offer cost-effective, innovative solutions with short delivery times. To achieve this, Paragon strategically maintains safety stock levels and fosters a robust, supportive supply chain. However, the company retains core operations, such as Research and Development (R&D), to mitigate operational risks.

A key aspect of Paragon’s strategy involves maintaining flexible and reasonably low costs. This is achieved by allowing a reasonable risk premium for its suppliers to ensure supply chain stability. Notably, Paragon views its relationships with suppliers as partnerships rather than merely transactions. This approach fosters an ideal win-win-win situation where clients receive products of satisfactory quality at reasonable costs, while both Paragon and its suppliers realize reasonable profits.

Product Portfolio

Paragon primarily focuses on thermal products, constituting over 90 percent of its sales. These products encompass standard heatsinks, heat pipe heatsinks, and vapor chamber heatsinks. Initially, Paragon’s business primarily revolved around casting products, which now constitute less than 10 percent of its sales.

Thermal products serve a vital role across various electronic devices due to prevalent thermal issues. During the product design phase, engineers meticulously address thermal concerns. Simultaneously, Paragon’s sales team collaborates with clients to refine heatsink specifications, including drawings, materials, delivery schedules, and cost parameters. This proactive engagement lays the foundation for meeting client expectations and ensuring customer satisfaction.

The lifecycle of Paragon’s products spans longer durations compared to rapidly evolving consumer electronic (3C) products. This extended lifecycle allows Paragon to accumulate more raw materials and maintain larger inventories of finished goods as safety stock. This strategic preparedness facilitates swift responses to client orders.

However, operating within a niche market presents challenges. While the slower technological evolution benefits Paragon, it also exposes the company to obsolescence issues. Unlike in the 3C market, Paragon’s clients do not
typically provide advance notices regarding product phase-outs or discontinuations. Consequently, the company of-
ten faces surplus materials or finished goods when products are discontinued, requiring independent resolution by Paragon.

**Production and Sales Process**

Paragon’s production cycle for its products spans approximately one to three months upon receiving client orders, averaging around two months. This duration, contingent on product complexity, is notably shorter than that of its competitors, aligning with Paragon’s strategy to prioritize customer satisfaction.

However, despite the slower technological evolution, clients often issue engineering change notices during the product lifecycle, leading to the obsolescence of certain sub-parts that become inapplicable for production. This necessitates further strategies for addressing obsolescence issues. Additionally, Paragon encounters challenges regarding sales forecasting as clients are hesitant to provide such information. Consequently, the company independently formulates procurement and production plans upon receiving purchase orders. Figure 1 encapsulates the primary production procedures adopted by Paragon.

**Scenario**

At the end of each fiscal year, Victor, the warehouse manager at Paragon, diligently compiles a comprehensive list of idle inventory items that have remained unsold for three years. This list is subsequently handed over to Nancy, the sales manager, who meticulously reviews the potential for future sales. Upon completion of this assessment, the warehouse collaborates with the accounting department, led by Mike, to facilitate the scrapping process for these identified items.

During a routine management meeting, the executive team convened to deliberate on the recurring challenge posed by idle inventories. In this meeting, the team explored the viability of incorporating technological interventions to address this persistent challenge.

Terry (General Manager): “Our company’s long-term goal involves aspiring to become a public or even a listed company. Despite our discussions on ESG, sustainability, and zero waste production, the accumulation of scrapping inventories persists annually. Isn’t it time we explore technological solutions to address this?”

Victor (Head of Warehouse): “While IT solutions sound promising, I must admit my limitations in this domain. I’m supportive if someone else steps forward to lead this initiative.”

Nancy (Sales Manager): “Agreed. My focus revolves around daily sales operations, prioritizing customer satisfaction. Given the complexity, I believe this task aligns more closely with accounting. Mike, what’s your take?”

Mike (Accounting Manager): “In our discussions during the last annual audit with our CPA, Henry, the potential of CAATs was highlighted as a tool to enhance output quality. Henry mentioned its recent incorporation of machine learning, suggesting its potential to aid in predictive analysis. I could consult Henry for more details on its applicability to our inventory issue.”

Terry: “Excellent. Let’s aim for positive outcomes in our next meeting. Remember, company performance aligns with our mission, and integrating sustainability is equally crucial.”
The main goal of this teaching case is to actively contribute towards reducing the expectation-performance gap in accounting education. The CAATs with embedded AI functions will optimize the predict analytic process with so-called, No-Code AI (Dilmegani, 2022). It means using a no-code development platform with a visual, code-free, and often drag-and-drop interface to deploy AI and machine learning models. Therefore, students are expected to:

1. *improve their soft skills: familiar with the CAATs tool*
   (1) articulating the issues at hand effectively,
   (2) engaging in analytical thinking to generate actionable recommendations,
   (3) communicating and presenting machine learning concepts, methodologies, and findings to both technical and non-technical audiences, and
   (4) fostering a mindset of continuous learning in the rapidly evolving field of machine learning.

2. *improve their hard skill:*
   (1) understanding the basic principles and concepts of machine learning,
   (2) understanding the algorithm of machine learning,
   (3) preparing the data for machine learning,
   (4) gaining familiarity with the intricacies of the machine learning tool,
   (5) exploring real-world applications of machine learning in various domains, and
   (6) evaluating the most appropriate model for a given problem and interpreting the outcomes.
Furthermore, this teaching case reflects a real-world scenario, conducting it as a group assignment could foster collaboration and diverse perspectives. Regardless of students' experience levels, structuring the curriculum across two weeks for introduction and application, three weeks for group discussions and solution development, and one week for presentations could be beneficial. Instructors or teachers should consider allocating time for this teaching case based on student experience, class size, and learning objectives. Approximately 5-10 hours may be needed to create teaching materials before the class and 2-3 hours may be devoted per class to teaching and assessment during and after the class, respectively. Additionally, a comprehensive approach is necessary in grading such teaching case, allocating weightage of 30-40 percent for concept comprehension like quizzes and written assignments, another 30-40 percent for practical application like exercises outlined in Appendix III, 20-30 percent for critical thinking, and 10-20 percent for communication and presentation would align with the learning objectives.

5 | IMPLEMENTATION OF THE CASE

Before implementation

This case is specifically designed for accounting undergraduates with limited professional experience. Therefore, students are required to familiarize themselves with ESG issues, such as e-waste and obsolescence, along with the utilization of a CAATs tool—a specialized software aiding auditors and accountants in data analysis and predictive modeling.

Moreover, emphasis on soft skills encompassing communication, critical thinking, problem-solving, and business management is crucial. Proficiency in these skills not only facilitates successful completion of this case but also augments students’ preparedness for their future careers. Instructors should allocate sufficient study time for these topics and may consider grouping students separately to encourage further discussion, based on a detailed implementation plan tailored to individual needs.

The implementation

The detailed implementation steps for machine learning are outlined in Appendix I. Instructors are encouraged to walk students through each step during class sessions, introducing the options available and their respective functions. Additionally, hands-on practice sessions should be conducted to familiarize students with machine learning techniques.

It’s important to note that accounting students might not have prior understanding of the functionalities and calculation algorithms inherent to machine learning. Therefore, instructors should consider briefing students on these aspects during class sessions or assigning related material as homework to enhance comprehension.

After implementation

Once students have successfully navigated the operational aspects and derived predictive outputs using machine learning, the pivotal phase of this teaching case emerges. Students are encouraged to delve into the role of an accounting manager, offering comprehensive suggestions based on their findings. It is imperative for them to consider how to effectively engage with the management team.

Given the potential involvement of obsolescence management with clients and suppliers, anticipatory discussions and
negotiations with external partners are foreseeable. To simulate these scenarios effectively, it would be advantageous and engaging to organize students into distinct groups for role-playing sessions. These sessions can serve as a platform for students to collectively strategize and articulate their final proposed solutions.

6 | CONCLUSIONS AND RECOMMENDATIONS

This teaching case on machine learning illustrates the step-by-step process of predicting potential obsolescence parts utilizing CAATs integrated with AI capabilities. It emphasizes the essential soft skills vital for enhancing management performance and obsolescence management. The systematic exploration of machine learning concepts, algorithms, and applications showcases the technology’s substantial potential in solving intricate problems. Additionally, by addressing student challenges and employing experiential teaching methods, improvements in engagement, knowledge retention, and critical thinking skills are anticipated.

The integration of technology, collaborative learning, and real-world scenarios proves highly effective in boosting student motivation and fostering a deeper understanding of the subject matter. This case equips instructors and students alike with the necessary tools and skills to navigate the dynamic landscape of machine learning. It empowers students to embrace active and lifelong learning.

Colleges and universities should consider updating their curricula to incorporate this emerging technology and experiential learning concept to enhance educational experiences and academic success. Furthermore, the accessibility of open data through the Open Data Movement offers an opportunity for readers to identify and address real-life issues using available data.

While reports suggest the susceptibility of accountants or auditors to automation, experts highlight that AI’s strength lies in automating repetitive tasks and minimizing errors, yet it lacks the capability for strategic decision-making (Mortensen, 2022). Hence, accountants and auditors must adapt to working alongside AI, overcoming forthcoming challenges, and delivering high-value work in the AI Era.
References


APPENDIX A

IMPLEMENTATION OF A MACHINE LEARNING CASE BY USING CAATs

As an ESG auditor tasked with waste management auditing for an electronic manufacturing company, proficiency in using CAATs tools becomes essential, much like it is for many auditors in today’s landscape. The machine learning capabilities within CAATs stand out as an efficient means to predict potential scrapping of finished goods or parts. Typically, a 3-phase method is employed in processing machine learning tasks (Huang et al., 2020) when utilizing the latest CAATs tools equipped with machine learning functions. Both ACL (Diligent, 2023) and JCAATs (Jacksoft, 2023) feature new machine learning commands like ‘TRAIN’ and ‘PREDICT,’ tailored for predictive analytics, making them viable options for this scenario. Figure 2 illustrates the primary predictive analytic process.

![Figure 2: The 3-phase method for processing machine learning](image)

**Phase 1: Data Preparation**

One well-known concept in computer science is “garbage in, garbage out” indicating that incorrect input leads to flawed outcomes. Therefore, the initial and pivotal step in any machine learning endeavor is data preparation, involving importing, validating, and exploring the data. You’re provided with two Excel files from the company to kickstart your process:

*International Journal of Computer Auditing, Vol.5, No.1, Publication date: 2023*
1. the inventory movements from November 2018 to October 2019 (Inv_train.xlsx) which contains 18,777 records.
2. the current inventory movements (Inv_pred.xlsx) containing 1,755 records.

Both sets of inventory data are sourced from the company's ERP system. Table 1 details the data structure for this task, while Table 2 outlines explorations of the TEXT fields data. Here's a breakdown of the data preparation steps for the machine learning case:

Step 1: To create a new project named Waste_Audit.

Step 2: To import both tables into the project.

Step 3: To validate the fields of each table.

Step 4: To explore each field of training table to ensure its suitable for the training by classification.

**Table 1: Data Structure**

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Data Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>DATETIME</td>
<td>The inventory movement during the month</td>
</tr>
<tr>
<td>Part No</td>
<td>TEXT</td>
<td>The number for each part</td>
</tr>
<tr>
<td>Product Category</td>
<td>TEXT</td>
<td>Category e.g., 1: Material; 5: Finished Goods</td>
</tr>
<tr>
<td>Product Code</td>
<td>TEXT</td>
<td>Code for segment of parts</td>
</tr>
<tr>
<td>Supplier</td>
<td>TEXT</td>
<td>Outsourced supplier except for “63” as inhouse part</td>
</tr>
<tr>
<td>BeginQty</td>
<td>NUMERIC</td>
<td>Quantity of beginning inventory</td>
</tr>
<tr>
<td>BeginAmount</td>
<td>NUMERIC</td>
<td>Dollar amount of beginning inventory</td>
</tr>
<tr>
<td>Pur. Qty</td>
<td>NUMERIC</td>
<td>Quantity of parts purchased</td>
</tr>
<tr>
<td>Pur. Amount</td>
<td>NUMERIC</td>
<td>Dollar amount of parts purchased</td>
</tr>
<tr>
<td>Other Add. Qty</td>
<td>NUMERIC</td>
<td>Quantity of other add. to inventory, like sample</td>
</tr>
<tr>
<td>Other Add. Amount</td>
<td>NUMERIC</td>
<td>Amount of other add. to inventory, like sample</td>
</tr>
<tr>
<td>Sales Qty</td>
<td>NUMERIC</td>
<td>Quantity Sales</td>
</tr>
<tr>
<td>Sales Amount</td>
<td>NUMERIC</td>
<td>Dollar amount of Sales</td>
</tr>
<tr>
<td>Other Deduct. Qty</td>
<td>NUMERIC</td>
<td>Quantity of other Deduct to inventory, like scrap</td>
</tr>
<tr>
<td>Other Deduct. Amount</td>
<td>NUMERIC</td>
<td>Dollar amount of other Deduct to inventory, like scrap</td>
</tr>
<tr>
<td>Ending Qty</td>
<td>NUMERIC</td>
<td>Quantity of Ending inventory</td>
</tr>
<tr>
<td>Ending Amount</td>
<td>NUMERIC</td>
<td>Dollar amount of Ending inventory</td>
</tr>
<tr>
<td>Scrapped</td>
<td>TEXT</td>
<td>“0” for not scrapped; “1” for scrapped</td>
</tr>
</tbody>
</table>
Table 2: Explorations of the Text Data

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Part No</th>
<th>Product Category</th>
<th>Product Code</th>
<th>Supplier</th>
<th>Scrapped</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classified Count</td>
<td>1,790</td>
<td>5</td>
<td>41</td>
<td>69</td>
<td>2</td>
</tr>
</tbody>
</table>

**Phase 2: Training Prediction Model**

In this case, we intend to predict the "Scrapped" signal in the current inventory movement data, aiming to prevent e-waste and promote SDG13 climate-action practices within the company. To achieve this, we'll use historical data as the training dataset to develop a prediction model for the "Scrapped" signal, focusing on the "Scrapped" field in the Inv_train table. The selection of suitable fields for the training process will vary depending on the specific context of the field and its relevance to the target field.

Our primary objective is to train CAATs' machine learning functions to prioritize the Product Category, BeginAmount, and BeginQty fields. These fields are potentially more relevant to the "Scrapped" category. However, we also encourage students to explore and select other fields for training, fostering a comprehensive understanding and building a more robust prediction model during their exercise.

The Train Command, an integrated machine learning function in modern CAATs or AI tools, streamlines the training process. Figures 3 and 4 display the interfaces of the TRAIN command in ACL audit software and JCAATs audit software, tailored specifically for this case.

![Figure 3](image-url)  
**Figure 3** The Train Interface of the Case in ACL Audit Software

After setting the target and training fields and running the Train command, students should tackle two key questions:
"How do we understand and elucidate the learning process?" and "How do we evaluate the training outcomes?"

In Figure 5, you'll see the ACL audit software's pipeline post-training, while Figure 6 illustrates JCAATs audit software's pipeline before training.

When pondering the learning process, students should explain how machine learning algorithms analyze training data to uncover patterns or relationships. Understanding basic algorithms like decision trees, neural networks, or random forests is crucial. They should explain how these algorithms process data to make predictions. Additionally, students should demonstrate their reflective thinking skills by providing a well-rounded assessment of the training results, highlighting both strengths and weaknesses of the model they've built.

Students need to address these questions:

Q1: What does "Pipeline" refer to in this Machine Learning Process?

Q2: Can you explain Machine Learning Algorithms, like "RandomForest," for instance?
To assess the training outcomes effectively, students need to take a structured approach. This involves studying the Confusion Matrix of the prediction model, considering metrics like accuracy, precision, recall, or F1 score. They should explore techniques like cross-validation to see how well the model generalizes and to spot any potential overfitting. Also, they should carefully analyze any limitations or biases in the training data that might affect the model's performance. This means looking at how outliers, data quality issues, or unbalanced datasets could impact accuracy and reliability. Figure 7 shows the Confusion Matrix in the JCAATs audit software specific to this case. Students should keep in mind that due to variations in training duration and the learning process, the machine learning performance metrics might display slightly different results.
Students need to answer these questions:

Q3: What is the “Confusion Matrix”?

Q4: What does it mean when we talk about “Accuracy,” “F1,” “Precision,” and “Recall”? In your training results, what values do these indicators show, and do they signify whether the prediction model is doing well or not?

Q5: What’s the significance of the “Importance” indicator in the training summary report? How can you explain the values associated with the respective fields?

**Phase 3: Prediction**

**Predicting Model Selection**

In the third phase, Prediction, students move on to model selection after the training phase wraps up. The model generated during training gets saved as a model file. Depending on the CAATs software used, these files might have different extensions – for instance, ACL could use “.model” while JCAATs might use “.jkm”.

For predictive analytics, students should import the dataset called “Inv pred.xlsx” that holds 1,755 records. They also need to choose the appropriate knowledge model file to start the prediction process. Once predictions are generated (shown in Figure 8), it’s time to analyze the results to evaluate their accuracy and reliability.
When diving into Predicting Result Analysis, students should gather key insights into how their predictive models perform and where they might fall short. As part of the hands-on learning approach, students need to tackle the following questions for the final report. They should really dig deep, think critically, consider different angles, and even explore further to enhance their understanding.

Q6: What do the "predicted" and "probability" fields mean?

Q7: What’s the total predicted Ending_Amount for scrapped inventory?

Q8: Can you identify the top three predicted Ending_Qty for scrapped parts?

Q9: Which supplier is linked to the highest BeginAmount of predicted scrapped inventory?

Writing a Predictive Analytic Report

The Predictive Analytic Report is the final stage of machine learning, presenting the findings from predicting potential parts at risk of being scrapped. This analysis aims to enable proactive strategies in this scenario. The United Nations, alongside Member States, have embraced the ambitious agenda of the SDGs 17. These goals encompass ending poverty, safeguarding the planet, and ensuring prosperity by 2030. Managing e-waste effectively aligns with several SDGs, including Goal 6 (Clean Water and Sanitation) and Goal 12 (Responsible Consumption and Production). Proper e-waste management reduces adverse impacts on human health and the environment, emphasizing the need to reduce waste generation with proactive solutions. This teaching case exemplifies how optimizing inventory management can
minimize losses linked to obsolete parts, contributing to long-term company success and global sustainability.

With the insights gained from predictive analytics and the responses to the earlier questions, there's confidence in the machine learning-generated output. This model can be effectively used to forecast future obsolete inventories, thus preventing material waste. Students are prompted to address the following question:

Q10: Based on the predictive analytics, suggest actions to prevent scrapped inventory.

(Appendix II provides the reference answers for the listed questions.)
APPENDIX B: The Reference Answer

The reference answer to questions about machine learning

Q1: What does "Pipeline" refer to in this Machine Learning Process?

**Answer:** In machine learning, the pipeline refers to the sequence of steps involved in training and deploying a model. It covers various tasks aimed at preparing and transforming data to enhance the model's performance. Some typical components of a machine learning pipeline include:

1. Handling Missing Values: This step deals with managing missing data in the dataset. Techniques like imputation (replacing missing values with estimated ones) or eliminating rows/columns with missing data are commonly used.
2. Encoding Categorical Text Data: When working with categorical variables, text data needs to be converted into numerical representations. One-hot encoding creates binary features for each category, while label encoding assigns unique numerical labels to categories.
3. Addressing Data Imbalance: Many datasets have imbalanced class distributions, which can impact model training. Techniques like using specialized algorithms such as SMOTE can help balance the dataset for better training.
4. Data Splitting: Dividing the dataset into training and testing subsets is vital for evaluating model performance. Common approaches include an 80/20 or 70/30 split for training and testing, respectively. Techniques like random splitting or k-fold cross-validation are often used.

These tasks represent a few examples within a machine learning pipeline. The specific steps and methods employed can vary based on the problem at hand, dataset characteristics, and the chosen algorithms.

Q2: Can you explain Machine Learning Algorithms, like "RandomForest," for instance?

**Answer:** The RandomForest algorithm is essentially a blend of multiple randomized decision trees that aggregate predictions through averaging them. Its development aimed to tackle the shortcomings of the decision tree algorithm (Blau & Scorne, 2016). RandomForest is widely acknowledged as one of the most popular machine learning algorithms, valued for its adaptability in both classification and regression tasks. The appearance of the "randomforestclassifier" in the pipeline screenshot confirms the use of the random forest algorithm in the machine learning process, offering detailed insights into its computations.

Q3: What is the "Confusion Matrix"?

**Answer:** In the field of machine learning, a confusion matrix (as shown in Figure 9) is a specific table layout that is often used to evaluate the performance of a model and provides a summary of the model's predictions and compares them to the actual values in the dataset (Draelos, 2019).
Q4: What does it mean when we talk about "Accuracy," "F1," "Precision," and "Recall"? In your training results, what values do these indicators show, and do they signify whether the prediction model is doing well or not?

Answer: In machine learning, metrics like 'Accuracy,' 'F1,' 'Precision,' and 'Recall' provide insights into how well an algorithm or model performs. To better interpret the implications of the figures from the previous phase, Table 3 presents the confusion matrix for this case.

Table 3: the Confusion Matrix of this case

<table>
<thead>
<tr>
<th>Actual condition</th>
<th>Prediction condition</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive (P)</td>
<td>Positive (PP)</td>
<td>TP=14</td>
</tr>
<tr>
<td>Negative (N)</td>
<td>Negative (PN)</td>
<td>FN=17</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FP=2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>TN=1,590</td>
</tr>
</tbody>
</table>

Explanation of these metrics and how they're calculated are list below:

(1) **Accuracy** is the ratio of number of correct predictions to the total number of input samples. It is simple to calculate and easy to understand but has its limitations when the data set is highly imbalanced.

(2) **Precision** measures correctness in true predictions, calculated as the ratio of correctly classified positive classes to the total predicted positive classes \((\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}})\). When False Positives significantly impact decision-making, Precision becomes crucial, and higher values indicate better model performance.

(3) **Recall** gauges actual observations correctly predicted \((\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}})\). In scenarios where False Negatives are critical, Recall becomes pivotal, and higher values signify better model performance.

(4) **F1 Score** is the harmonic mean of Recall and Precision \((\text{F1} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}})\). It balances Recall and Precision when one isn’t distinctly more important than the other. Particularly for imbalanced data with significant False Negatives and False Positives, higher F1-Scores are preferable.
The solutions and formula for the above questions are calculated as below:

\[
\text{ACCURACY} = \frac{TP+TN}{TP+TN+FP+FN} = 0.98917
\]
\[
F1 = \frac{2TP}{2TP+FP+FN} = 0.93907
\]
\[
\text{PRECISION} = \frac{TP}{TP+FP} = 0.98648
\]
\[
\text{RECALL} = \frac{TP}{TP+FN} = 0.89570
\]

The high values of these indicators suggest that the model is performing well, and there doesn't seem to be an issue with data imbalance that needs addressing.

**Q5:** What's the significance of the "Importance" indicator in the training summary report? How can you explain the values associated with the respective fields?

![Figure 10: The Summary Report](image)

**Answer:** The "Importance" indicator totals to 1 (equivalent to 100 percent). Therefore, when the "importance" value for the variable "BeginAmount" is 0.5089, it signifies that 50.89 percent of the training model is influenced by the variable "BeginAmount". In this instructional case, "BeginAmount" holds the highest value among all variables, indicating its pivotal role as the most influential variable in this predictive model. Additionally, variables with an "Importance" value of "0" are considered insignificant or irrelevant to this particular machine learning model.

**Q6.** What do the "predicted" and "probability" fields mean?

**Answer:** The "predicted" field displays the anticipated results generated by the "Waste train mod" model. Meanwhile, the "probability" field indicates the likelihood or confidence associated with the correctness of the corresponding outcome in the "predicted" field, derived from the "Waste train mod" model's predictions.

**Q7:** What is the total predicted Ending_Amount of scrapped inventory?

**Answer:** To determine the total predicted Ending_Amount of scrapped inventory, utilize the "Classify" command by summing the beginning quantity field with the Predicted field classification. The calculated predicted scrapped Amount is 20,437.50, when "Predicted" equals "1". The ACL software will display the resulting output as illustrated below.
Q8: Can you identify the top three predicted Ending_Qty for scrapped parts?

Answer: To identify the top three predicted Ending_Qty for scrapped parts, students can utilize the ACL software. By applying the “Sort” command with the filter “Predicted = 1,” they can identify the top 3 predicted quantities of scrapped parts, specifically part no. SP021_A000, 261-00-046, and .2CHNTZB0

Q9: Which supplier is linked to the highest BeginAmount of predicted scrapped inventory?

Answer: The supplier linked to the highest BeginAmount of predicted scrapped inventory is identified as ORA. Students can use the ‘Classify’ command, specifying the ‘Supplier’ as the key field, and the BeginAmount field as the subtotal to extract this information.

Q10: Based on the predictive analytics, suggest actions to prevent scrapped inventory.

Answer: Utilizing predictive analytics, the management team can adopt both proactive and reactive strategies. Reactively, they could address existing scrapped items by engaging with clients for potential sales or recycling. Proactively, the team can leverage machine learning to predict high-risk obsolete parts. By adjusting raw material purchases and safety stock levels, they can mitigate future obsolescence. Collaborating with clients and suppliers to negotiate for special sales promotions or explore alternative uses for obsolete materials further contributes to minimizing e-waste. This approach aligns with sustainable practices, enhances resource optimization, and showcases responsible business conduct.
APPENDIX C: EXERCISE

With the demonstration beforehand, we may know how to predict which part is most likely obsolete and going to be scrapped. The students are encouraged to practice with the datasets provided in the attachment for further practice. However, students are also encouraged to study some additional information or knowledge beyond the data and technical tools, such as the development of ESG, the status of E-waste, obsolescence management, critical thinking, machine learning, and so on. If there is instructor or teacher for this exercise, explanations, discussions, or tests might be necessary and helpful for the students before starting the exercise. Further, students are encouraged to practice the whole function of the tool they are going to use in this exercise for their long-term benefit.

The suggested steps of exercise are as follows:

1. Data preparation

Check each column of the training dataset ("Inv data for train") and prediction dataset ("Inv data for prediction"), and then import them into ACL and record the Data Type in the next table:

<table>
<thead>
<tr>
<th>Field Name</th>
<th>Data Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td></td>
<td>The date of inventory movement</td>
</tr>
<tr>
<td>Part No</td>
<td></td>
<td>Part No</td>
</tr>
<tr>
<td>Beg. Q</td>
<td></td>
<td>Quantity of beginning inventory</td>
</tr>
<tr>
<td>Beg. Amount</td>
<td></td>
<td>Amount of beginning inventory</td>
</tr>
<tr>
<td>Pur. Q</td>
<td></td>
<td>Quantity of purchasing inventory</td>
</tr>
<tr>
<td>Pur. Amount</td>
<td></td>
<td>Amount of purchasing inventory</td>
</tr>
<tr>
<td>Sales Q</td>
<td></td>
<td>Quantity Sales</td>
</tr>
<tr>
<td>Sales Amount</td>
<td></td>
<td>Number of Sales</td>
</tr>
<tr>
<td>Ending Q</td>
<td></td>
<td>Quantity of Ending inventory</td>
</tr>
<tr>
<td>Ending Amount</td>
<td></td>
<td>Amount of Ending inventory</td>
</tr>
<tr>
<td>Scrapped</td>
<td></td>
<td>“0” for not scrapped; “1” for scrapped</td>
</tr>
</tbody>
</table>

Table 4: Record of Data Structure
2. Training Prediction Model

Try to train the dataset “Inv train” with different factors and make and record the training factors used for the training in Table 5 with check mark “✓” and fill in the training output of each try in the next table. Keep training the data with different combination of factors until the student could find out an optimal training result based on the record.

<table>
<thead>
<tr>
<th>Training Inputs</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Part No</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beg. Q</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beg. Amount</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pur. Q</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pur. Amount</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales Q</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales Amount</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ending Q</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ending Amount</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scrapped</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Training Outputs</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOGLOSS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACCURACY</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AUC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRECISION</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RECALL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3. Training Evaluation

Based on the training output in the above, to evaluate which machine learning model would be more proper for prediction. Normally, the higher the Training Outputs are, the proper the training model is. And the students are encouraged to learn more about ACL or Machine Learning for a better decision in evaluation, or the students are welcomed to visit the website of International Computer Auditing Education Association (ICAEA) for free E-Learning Courses (https://www.icaea.net/English/Training/CAATs_Courses_list.php) or teaching cases regarding machine learning on the website of the ICAEA (https://www.icaea.net/English/Publication/Journal_2020.php).

4. Prediction

Use the best training model after training evaluation to predict and fill in the confusion matrix below Table 6:

<table>
<thead>
<tr>
<th>Actual condition</th>
<th>Prediction condition</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive (P)</td>
<td>TP=</td>
<td></td>
</tr>
<tr>
<td>Negative (N)</td>
<td>FP=</td>
<td>TN=</td>
</tr>
</tbody>
</table>

5. Prediction Result Evaluation

To calculate the value and fill in the next table and evaluate the prediction output:

Table 7: Evaluation of Prediction

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCURACY</td>
<td></td>
</tr>
<tr>
<td>AUC</td>
<td></td>
</tr>
<tr>
<td>PRECISION</td>
<td></td>
</tr>
<tr>
<td>RECALL</td>
<td></td>
</tr>
</tbody>
</table>
6. Conclusions and suggestions

With the outputs from this exercise, students are expected to make the conclusion and give detailed suggestions if they were the accounting manager and think about the potential responses from the sales manager, other counterparties, or even the CEO. Furthermore, the instructor or teacher, if any, could make it as case of experiential learning and separate students into different groups and ask students to discuss about the outputs from different perspectives.

Attachment 1: Training Dataset "Inv train.xlsx"

Attachment 2: Predictive Dataset "Inv pred.xlsx"