SBIR Phase II: AutoEdge: A Hardware-aware AutoML Platform for Resource-Constrained Devices

Administrative registrations

- ☐ Dun and Bradstreet Data Universal Numbering System (DUNS)
- ☐ System for Award Management registration
- ☐ Research.gov
- ☐ Small Business Administration (SBA) Company registration

Proposal submission on research.gov

- ☐ Project Summary [One (1) page max].

Project Description. -Fifteen (15) pages max-

- ☐ Market Opportunity
- ☐ Company/Team
- ☐ Product/Technology and Competition
- ☐ Finance and Revenue Model

Others

- ☐ 5 letters of recommendation
- ☐ Phase I technical narrative

1 Market Opportunity

1.1 Target Customer and Market Need

Through our **Beat-The-Odds-Bootcamp** participation, we conducted **over 100 interviews**, and AI POW identified our **beachhead market** to be **medium-sized manufacturing companies**. These businesses are **tech-forward**, typically employing between **100 and 500 individuals**, and are well-versed in advanced data warehousing solutions like **Snowflake, Redshift, or BigQuery**. The primary decision-makers, holding positions such as the **Head of Data and Analytics or Head of Engineering**, recognize the importance of effective **quality assurance** and **anomaly detection and resolution** within their operations. Despite acknowledging these necessities, they face a significant challenge due to a **scarcity of data analysis and data science expertise**, which leads to **bottlenecks in data interpretation**. This problem is even more acute regarding successfully implementing **real-time visual inspection**, highlighting the critical need for solutions in this space.

After a rigorous **beachhead analysis**, our team has been able to qualify our leads effectively, leading to fruitful collaborations with three key early customers, **Daikin** [1], **Sakaiya** [2], and **American Innovations** [3], as seen in Fig. 1. All of these organizations fall within our identified target market, illustrating the specific challenges and needs we aim to address. Daikin, Sakaiya, and American Innovations operate in the manufacturing sector, and like many companies in this industry, they confront substantial challenges tied to **automated quality assurance**. Below we present a more detailed analysis of our target customer and pinpoint their market need.

Daikin is the global leader in air conditioning, with HVAC&R, fluorochemical, and filtration products. Daikin's product line range from residential to industrial. Daikin is constantly innovating, and developing new products with future air innovations with a reduced impact on the environment. One pain point that even Daikin as a global leader has is the shortage of data scientists, one of their Failure Analysis Engineers mentions: *"The adoption of AutoEdge in exploration of internet-enabled HVAC sensor data points will revolutionize our approach to data analysis, specifically in the realm of anomaly detection. What traditionally requires over 18 hours to complete can now be achieved in under 30 minutes, thanks to AutoEdge's sophisticated automation and machine learning techniques." (Letter of support 1. Mr. Aquilino Rodriguez, Failure Analysis Engineer.* **Daikin**.)

Sakaiya specializes in manufacturing car dashboards and grapples with the persistent challenge of maintaining a high level of product quality. The company has identified an urgent need for improved data analysis methods as they strive to **optimize their manufacturing process** to reduce defective parts to less than 1%. One of the issues they face is the need for manual visual inspections, which has increased the inspection team size from three to five individuals per production line. This additional personnel has inflated their **annual expenses by over $100,000**. This pressing concern was underscored by our collaborators at Sakaiya who articulated the scale of this challenge, noting: *"Sakaiya has been a customer of AI POW LLC since Q1 of 2023, and we have witnessed firsthand the transformative effect of their product, AutoEdge, on our operations. AI POW LLC has approached the field of data science, making it accessible to a broader audience and significantly improving our operational efficiency." (Letter of support 2. Mr. Ryuji Miyazono, CEO.* **Sakaiya***.)*

Figure 1: AI POW LLC early customers (top), investors (center), and new customer leads (bottom).

American Innovations, a manufacturer of pipeline corrosion assessment systems, **is tackling**

high miss-assessment rates, aiming to drop them to 1 in 50. These inaccuracies disrupt client workflows and **incur an additional $3,000 in weekly costs** highlighting that: *Our initial collaboration with AI POW LLC in Q4 of 2022 yielded solid results in a short time. In Q1 of 2023, American Innovations secured a contract to integrate AutoEdge into our handheld devices.(Letter of support 5. Mr. Andrew Holle, Principal Systems Architect.* **American Innovations, LLC***.)*

NetMind Ventures, our pre-seed investor, comments on solving such need are as follows: *We have observed their journey since our initial investment of USD $300,000 during the pre-seed funding round, and we can confidently affirm that their commitment to innovative solutions has only amplified. (Letter of support 4. Mr. Yu Cheng, Chief Research Office.* **NetMind Ventures***.)*

Additionally, a new partnership with Samsung Research America has just opened; this early collaboration is an example of the effectiveness of AI POW LLC's lead generation engine. Samsung comments on this partnership are: *Our preliminary discussions with AI POW LLC have fostered a recognition of AutoEdge's potential, particularly in the area of defect detection and machine learning explainability. We are excited about the anticipated enhancements in our operational processes that could stem from the integration of this promising tool. (Letter of support 3. Dr. Rui Chen, Senior Director.* **Samsung Research America***.)*

1.2 Current Enterprise Solutions

The anomaly detection landscape is populated with various AI-driven solutions, each with its unique strengths and limitations. Among these, Google's Visual Inspection AI [4] and Microsoft Azure's Anomaly Detector [5] stand out for their distinct capabilities.

Google's Visual Inspection AI, designed specifically for manufacturing, excels in defect detection with minimal label requirements. However, its application is constrained by a lack of open-source support, limitations for businesses with no pre-labeled data, and insufficient proficiency with time-series data curtails its broader applicability. On the other hand, the versatility of **Microsoft Azure's Anomaly Detector**, particularly in time-series anomaly detection, falls short of automated visual inspection, a feature crucial for many manufacturers. Furthermore, its technical complexity may create hurdles for non-technical users, adding to its adoption and implementation challenges. The complexity extends to integration, with potential difficulties and extended time-frames depending on an organization's existing IT infrastructure.

The ideal solution should support open-source, assist businesses without pre-labeled data, and offer automated visual inspection for manufacturers. It must also minimize technical complexity for ease of use and offer seamless integration to save organizational resources, thus addressing the broad needs of the manufacturing industry. Table 2 and section 3.3 presents a more in-depth competition landscape analysis.

1.3 Product Description & Expected Outcomes

AI POW's AutoEdge, is a Machine Learning (ML) based quality assurance platform designed to assist medium-sized manufacturers as seen in Fig. 2. Currently, AutoEdge is capable of detecting anomalies and defects in manufacturing processes. One of its key technological advantages is its hardware-aware characteristics that allow a fast and easy ML model deployment and inference, as well as the ability to produce synthetic data sets from limited amounts of labeled data, removing the need for large labeled data sets.

In Phase II our team proposes to build upon our Phase I work to use our customer feedback and respond to their needs by improving our hardware-aware technologies to include asset monitoring features that also provide a root cause analysis of the defects found in the production line. Our proposed Phase II work intends to offer actionable insights for enhancing efficiency by integrating the strengths of time-series analysis and automated vision inspection, thereby ensuring more precise anomaly detection and intuitive root cause analysis. The primary technology

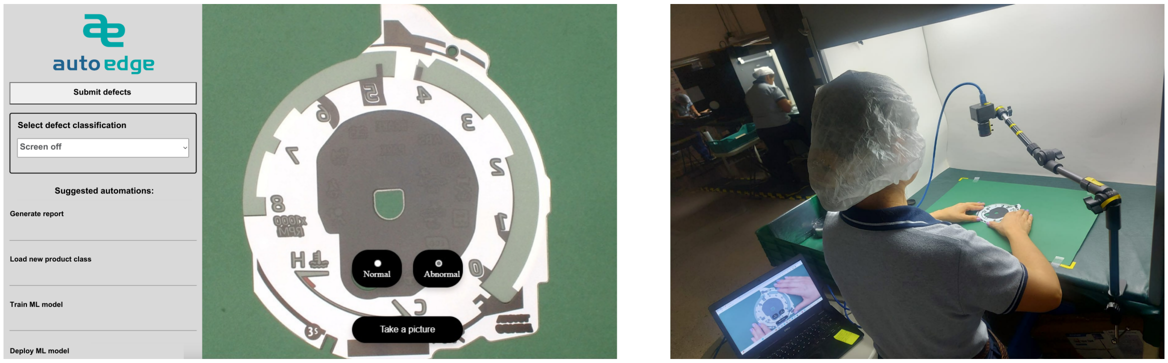

Figure 2: (Left) Showcasing AutoEdge v2.0, an advanced, hardware-aware platform identifying defects in a mass-produced car dashboard with its technologically superior processes. (Right) A dedicated quality inspector from Sakaiya, seamlessly incorporates AutoEdge in his workflow, accurately pinpointing manufacturing defects right at their end-of-line stage.

objectives and crucial milestones of AutoEdge focus on developing a hardware-aware platform for visual inspection and time series analysis. This model is designed to tackle the challenges inherent in multimodal complex data analysis involving computer vision and time series data.

The development of all tailored optimized machine learning pipelines, which includes data preprocessing, feature extraction, model selection, and compression, is needed to handle the challenges of multimodal complex data analysis. To this end, a highly modular AutoML system is currently being developed, incorporating the invaluable feedback obtained from the users of our proof-of-concept, AutoEdge v1.0. Given the intricacies of applying AutoML to multimodal complex data analysis, such as managing defined search spaces and learning objectives, we propose the implementation of automated pipeline searching, neural architecture search (NAS), and active search space. Such strategies are anticipated to mitigate high computational costs, enhance performance, and maximize label information usage.

Acknowledging the distinct characteristics and inherent variability of multimodal complex data analysis across various data types and applications, our methodology merges scientific R&D in computer vision and time series data with a feedback-oriented build-measure-learn loop. This strategic approach enables us to deliver custom-engineered solutions within our system, rooted in our previous research on ML automation and complex data types, while maintaining a customer-centric lean methodology. To further progress this project, we plan to leverage tree-based algorithms and knowledge graph reasoning in ML, with an emphasis on the development of a hardware-aware model for time series analysis. Our comprehensive strategy ensures the robustness of our solution and its ability to navigate the unique challenges associated with our interpretability goals. A pivotal feature proposed in Phase II is AutoEdge's asset monitoring capability, this tool empowers domain experts to analyze time series data, irrespective of their data science or computer science expertise. Our new proposed work streamlines data pre-processing, eliminating the need for manual data cleaning, identifies information-rich attributes, and detects anomalies within the dataset. Furthermore, it provides visual feature contributions, ranking crucial features, and alleviating data overload by presenting only the most impactful data to users.

Below is a list highlighting key goals achieved during Phase 1:

Phase I Objectives	Expected Measure of success	Actual Measure
Improve Anomaly Detection in Manufacturing	Improve defect detection by at least 20%	50% improvement
Reduce need of labeled data	100 samples required for model training	Less than 20 samples needed
Active customers using AutoEdge tool	At least 1 customer	3 customers
Revenue target (product-market fit)	$50k	$150k+

Additionally, the following table introduces key development objectives for Phase II:

Phase II Objectives	Expected Outcomes	Estimated timeline
Root cause analysis integration	Enable domain experts to solve problems under 1 hour	2025 - Q1
Increase Tool Adaptability across Various Manufacturing Sectors	Onboard at least three manufacturers from different sectors	2024 Q2
Annual Recurring revenue	$100k	2026 - Q1
New private investment	$2MM	2023 - Q4

At the onset of Phase II, AI POW LLC's products will revolutionize the manufacturing sector globally, becoming an indispensable tool for defect detection. Our robust system will empower manufacturers to **automate defect identification from day one, bypassing the burdensome costs and delays of traditional data labeling processes**. More than a mere detection tool, AutoEdge aims to provide a comprehensive understanding of the root causes of these defects. Our **complex-data analysis engine and intuitive design will ensure that domain experts, irrespective of their data science acumen, can decode the origins of the defects swiftly, making necessary amendments within a quarter of an hour**. In essence, AutoEdge seeks to combine efficiency, accessibility, and immediacy, radically improving operational flow in manufacturing while requiring minimal technical expertise.

1.3.1 Business Model

Currently AutoEdge operates on a combined Non-recurring Engineering (NRE) fee and subscription model for its image defect detection and time series machine learning models. The current NRE fee is set at $80,000, which covers the cost of the initial setup, customization, and system implementation. Following this, a recurring subscription fee of $2,000 per month per license includes ongoing maintenance and support.

This business model offers several advantages. Firstly, the upfront costs for the customers are lower, making the platform more accessible to a wider range of businesses, including medium-sized manufacturers. This is particularly important in industries where the initial capital investment can often hinder adopting new technologies. Secondly, the recurring subscription model provides a steady and predictable revenue stream for AutoEdge. This makes forecasting revenue easier and planning for future growth and development. It also aligns with the ongoing value that customers receive from the platform, as they benefit from continuous updates, maintenance, and support. Lastly, this business model supports scalability. With the aim of low cost and high volume, AutoEdge can effectively scale its operations to meet the growing demand for AI-powered quality assurance in various industries. This scalability is beneficial for AutoEdge's growth and ensures that as the customer's business grows, AutoEdge's solutions can grow with them.

As seen in Fig. 3, our tool's Value flow consists of the following components. **Who Buys**: Manufacturing companies are the primary customers. **Who Sells**: Sales occur directly from AutoEdge or through its strategic partners. **Software Access**: Customers access our cloud-based platform, negating the need for physical installations. **Cloud Service**: We utilize Amazon Web Services for our robust cloud capabilities. **Delivery of Value**: Access to AutoEdge's platform is granted once the purchase is formalized. **Use of Software**: The platform is ready to accept and process the customer's manufacturing data. **Value Realization**: Immediate value is delivered via our real-time defect detection and in-depth analysis capabilities, providing customers with actionable insights from the get-go.

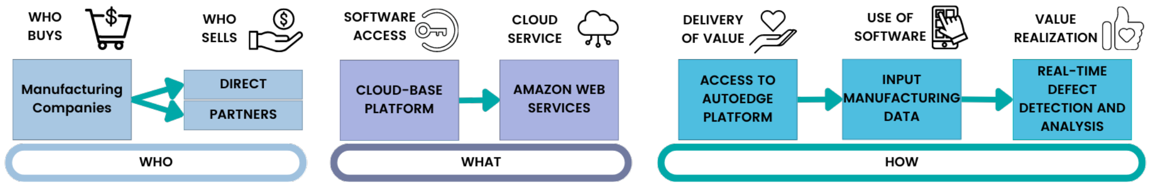

Figure 3: AI POW LLC Value flow for product AutoEdge

1.4 Target Market

The market size and growth analysis for AutoEdge is based on the report "Automated Machine Learning (AutoML) Market," by MarketsandMarkets [6]. Our Total Addressable Market (TAM) stands at $558.5 million in 2023, which is the US Market 2023 for AI applied to Manufacturing.

Country	**2022**	**2023**	2024	2025	2026	2027	CAGR (2022-2027)
US	380.1	558.5	813.0	1,187.5	1,749.2	2,587.4	46.8%

Our Serviceable Addressable Market (SAM) was derived assuming that we will focus on Quality Control in AutoML, which is approximately 16.6% of the market = $92.7 Million with a 46.3% CAGR supported by the following:

Sub-Vertical	2023	2024	2025	2026	2027	2028	CAGR (2023-2028)
Quality Control	17.3	25.9	38.4	56.3	81.4	116	46.3%

Our Serviceable Obtainable Market (SOM) will include the following industries within manufacturing (those that could be addressed by AutoEdge's services' current capabilities): Semiconductor & Electronics, Energy & Power, Automotive, Heavy Metals & Machine Manufacturing, and others. These industries are 79.5% of the AI application in manufacturing, and vertical Quality Control, which is approximately 107.8 million.

Industry	Proportion (%)						CAGR (2022-2027)
	2022	2023	2024	2025	2026	2027	
Semiconductor & Electronics	9.2	9.0	9.0	9.2	9.7	10.2	51.1
Energy & Power	17.9	17.4	17.2	15.8	15.7	16.2	45.0
Automotive	37.8	34.9	31.9	31.0	30.9	30.4	41.6
Heavy Metals & Machine Manufacturing	7.5	8.1	8.7	12.9	13.8	14.3	68.3
Others	7.2	10.2	12.5	10.1	8.6	7.0	48.8
Total	79.6	79.5	79.3	79.1	78.8	78.2	47.9

Example accounts that fit this target market and persona profile include Daikin, Sakaiya, and American Innovations. These companies represent the ideal customer profile for AutoEdge, demonstrating the type of businesses that can benefit from the platform's AI-powered quality assurance and anomaly detection capabilities.

Market entry barriers in this sector include insufficient resources to employ expert data scientists, sub-optimal data quantities for effective analysis, or the inherent uncertainties surrounding advanced data analytics. The latter's case-specific attributes can differ vastly across various hardware platforms and end applications, raising the potential for steep entry obstacles. To counteract these risks, our approach intertwines scientific R&D on IoT and AutoML with a build-measure-learn feedback loop, fostering close collaborations with our partners and their customers. This tactic empowers us to develop engineering solutions tailored to tackle the challenges, incorporating insights from our previous research on ML automation and embedded systems. This customer-focused lean methodology enables us to continuously refine our system.

1.5 Commercialization Strategy

AutoEdge's commercialization strategy centers around our offering tailored to mid-sized manufacturing firms, especially those with **50-500 employees**, established **post-2010** and utilizing technologies like Snowflake, Redshift, and BigQuery. Our target personas are the **Head of Failure Analysis, Head of Data and Analytics, and Head of Engineering**, particularly in smaller firms. Potential accounts of interest include **American Innovations and Sakaiya**. As shown in Fig. 4 we utilize a variety of communication and distribution channels such as 'Towards Data Science', GitHub, and **AutoKeras** (our open source proof-of-concept work), aiming to convert around 100 monthly customers of the monthly 240,000 AutoKeras visitors to premium users each month over the next five years. Our official website, AutoEdge.ai, provides an accessible platform to reach a wider audience and engage with our users. Furthermore, our revenue model comprises three key components: an average **$80k non-recurring engineering** fee per contract, and a **subscription-based pricing of $2,000** per seat that includes regular updates, support, and maintenance. This model fosters long-term partnerships, promotes customer loyalty, and allows for effective budgeting and cost management for our clients.

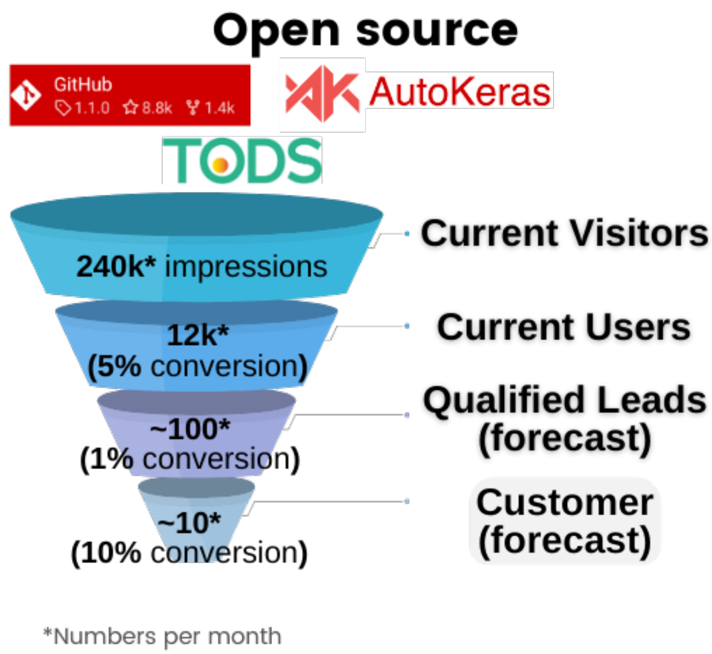

Figure 4: AutoEdge - commercialization strategy

1.6 Barriers to Entry

Market entry barriers for advanced data analytics in manufacturing industries, such as the need for expert data scientists, limited data quantities, and case-specific attributes, can pose significant challenges. This project proposes to mitigate these risks through a unique combination of scientific research and development in IoT and AutoML and a build-measure-learn feedback loop, effectively employing a customer-focused lean methodology. This approach enables continuous refinement of the system based on feedback from partners and customers. To stay updated with the latest industry trends and expand outreach, the team also plans to participate in key manufacturing conferences, including the IndustryWeek's Manufacturing & Technology Show and the American Manufacturing Summit, starting Q1 2024 [7,8].

2 Company/Team

2.1 Origins of company and Current Corporate Structure

AI POW LLC, established in 2019, is a vibrant startup born in the computer science department at Rice University. With a strong foundation in both academia and the open-source community, our team marries technical expertise, established AI credentials, and entrepreneurial spirit. This dynamic combination enables us to effectively transform our innovative vision into tangible business success. As part of our growth strategy, we are actively seeking to expand our team with the addition of a seasoned operations officer and an increased force of programmers.

2.2 Brief description of Company

As a venture-capital-funded entity, AI POW LLC is at the forefront of developing Artificial Intelligence (AI) technologies. Our key personnel are the driving force behind our ambitious project. Our leadership team includes CEO Dr. Alfredo Costilla-Reyes, CTO Dr. Xia "Ben" Hu, VP of Engineering Dr. Kwei-Herng "Henry" Lai, and VP of R&D Dr. Daochen “Frank” Zha. Providing strategic direction and expert advice are our technology advisor Mr. John Hanks and our business strategy advisors from NetMind Ventures [9] led by Mr. Yu Chen.

AI POW LLC’s financial strength is anchored in a diverse portfolio of funding sources, reflecting a strong foundation for future growth and expansion. Our capitalization consists of the following three elements: **(1) Equity Capital**: This constitutes the funds that have been invested in the company, amounting to a total of $300,000. **(2) Revenue**: Our company has generated a significant sum of $250,000 through our service contracts and consulting work. This income stream attests to our business’s marketability and profitability. **(3) Grants**: We have successfully secured a SBIR Grant totaling $275,889, demonstrating the recognition and support of our innovation from prestigious granting bodies. As such, the sum total of our **capitalization equals $825,889.** This robust capitalization, consisting of equity, revenue, and grants, underscores our financial sustainability and growth potential.

2.3 Financing and Revenue History

Below is our financing and revenue from 2021 (historic) to 2027 (forecasted):

Rev Source (in $ Thousands)	2021	2022	2023	2024	2025	2026	2027
NSF SBIR 1, 2 and 2B		275	500	500	500		
VC funding		300		2000			
Consulting	50	48					
University Funding – Rice University – Lilly Lab		15					
Revenue from Sales			98				
Partner Selling – SW subscription on companies’ behalf				1000	1500	2000	2500
Total	50	638	598	2500	2000	2000	2500

2.4 Team Background and Experience

Dr. Alfredo Costilla-Reyes, serving as our Chief Executive Officer, has a strong background in research and product development. He led the research in time-series anomaly detection and explainable AI for IoT devices, at our Hispanic-led company that spun off from Rice University’s Department of Computer Science. Dr. Costilla-Reyes is a trailblazer, being the first-generation graduate of both the Entrepreneurship and Technology Commercialization program at Mays Business School and the doctoral program in Electrical Engineering at Texas A&M University. His exceptional contributions to science, technology, and entrepreneurship have earned him numerous accolades including the prestigious Mexico's National Award. Dr. Costilla-Reyes' expertise in embedded software and systems, IoT applications, and wearable consumer electronics, coupled with his participation in esteemed entrepreneurial platforms like YCombinator's YC120 event.

Dr. Xia "Ben" Hu, is an Associate Professor at Rice University's Department of Computer Science, bolsters our team with his prolific contributions to data mining. His work has been widely recognized, resulting in over 100 published papers, seven Best Paper Awards (candidate), and notable awards such as the JP Morgan AI Faculty Award, the Adobe Data Science Award, and the NSF CAREER Award. Dr. Hu has played an instrumental role in developing AutoKeras, an open-source package which has gained immense popularity as an automated deep learning system on Github. His profound impact on AI is further evident in his work on deep collaborative filtering, anomaly detection, and knowledge graphs, which are being utilized in systems at TensorFlow.

Dr. Kwei-Herng "Henry" Lai, formerly associated with Academia Sinica, brings substantial industry collaboration experience to our team. He has spearheaded large-scale machine learning projects in partnership with industry leaders such as KKBOX, KKTIX, and Cathay United Bank.

Dr. Daochen "Frank" Zha, has worked as a Machine Learning Engineer at Meta (Formaly known as Facebook), Dr. Zha enriches our team with his expertise in reinforcement learning and machine learning systems.

Sonia Yu is a Business Developer and Strategy intern at AI POW LLC, where she strategically aligns the company's technological competencies with market opportunities and business objectives, shaping the organization's growth initiatives with her keen business acumen and understanding of the tech industry.

Yi Xu is a data analyst intern at AI POW LLC with advanced degrees in Statistics and Applied Mathematics. With a strong background in Python, R, SQL, and data visualization tools.

Experience and Skill Gaps: AI POW LLC's team is proficient in research, product development, and advanced anomaly detection technologies. However, there are areas for enhancement.
Front-End Development: Our expanding product offerings necessitate robust, intuitive interfaces. While we are skilled in backend and machine learning development, we require more front-end expertise. We plan to hire front-end developers experienced in creating user-friendly interfaces for complex technologies, ensuring both excellent function and user accessibility.
Hardware-Software Co-Optimization: Given our solutions' deployment across various hardware platforms, we recognize the need for hardware-software co-optimization. Although proficient in AIoT software development, we need more experience in software optimization for different hardware configurations. We aim to collaborate with hardware specialists and consider hiring professionals in hardware-software co-optimization.
Customer Success Management: As our customer base expands, ensuring successful customer onboarding and satisfaction is crucial. We plan to hire experienced customer success managers familiar with AIoT technologies to manage customer relationships effectively and ensure the alignment of our technical solutions with customers' needs.
Strategic Business Development and Marketing: We've made strides in carving a niche in the AIoT market but see room for improvement in strategic business development and marketing. We've engaged an MBA intern, Sonia Miyazono, and plan to hire experienced business development professionals while investing in targeted marketing strategies to expand our market presence and attract new customers.

AI POW LLC is supported by Kearney, McWilliams & Davis, PLLC, a law firm providing customized legal support in areas like business formation, development, and tax planning. Regardless of legal complexities, their expert counsel, proficient in regional, national, and global legal landscapes, prepares us to tackle any legal hurdles in our path to AI technology development and commercialization. This alliance bolsters our resources, reinforcing our forward trajectory.

3 Product/Technology and Competition

3.1 Value Proposition and Validation

We discovered in boot camp interviews that failure engineers often spend an excess of 18 hours analyzing anomalies. This laborious task is largely due to the lack of sufficient data science expertise within their teams which may be exacerbated by the absence of a dedicated data science team. AutoEdge empowers failure engineers to function effectively as data scientists, **irrespective of their previous exposure to computer science**. Specifically, the customers desired a solution that could allow the use of Machine Learning with minimal dependency on labeled data. Additionally, they need an automated system capable of complex data analysis, freeing up valuable human resources for other tasks. Lastly, customers want a tool that can identify anomalies, and help them understand the root cause. With minimal labeled data requirements, AutoEdge facilitates the analysis of products on a production line, simplifying defect detection, and aiding in comprehending the root cause of the problems identified. We addressed all the customers needs in our Features as shown in Table 1.

Our rigorous market analysis and solution development have already begun showing promising signs of achieving a solid product-market fit. We have secured major contracts with Sakaiya, American Innovations, and, most recently, Daikin, a testament to our commitment to solving this critical industry challenge. This marks a significant milestone for our company and emphasizes our dedication to providing solutions that address genuine market needs.

Feature	**Advantage**	**Benefit**
Dataset synthesis and augmentation	Leverages vast data sets, overcoming cold-start problem	Enables operations with less than 20 pre-labeled data samples
AutoML	Facilitates ML for medium-sized customers, no dedicated data science team required	Empowers custom ML models for unique challenges
Explainable AI	Provides automatic explanations for anomaly flagging decisions	Assists in resolving manufacturing line issues within 15 minutes

Table 1: Features, Advantages, and Benefits of AutoEdge's Technologies

Machine Learning with Minimal Labelled Data: Phase II technology will harness the power of ML while reducing the dependency on labeled data. This means that customers can get started with less data preparation, thereby speeding up implementation and yielding faster results. This feature directly translates to time and resource efficiency, making AI adoption easier for industries.

Automated Complex Data Analysis: Building upon the automation capabilities of Phase I, Phase II will offer an even more advanced system for handling complex data analysis. This feature will further free up valuable human resources, enabling companies to divert their expertise to more strategic tasks, thus improving operational productivity.

Enhanced Anomaly Understanding: In Phase II, the tool will not only identify anomalies but will also provide enhanced insights into their origins and nature. This helps companies better understand and address the root cause of problems, improving overall product quality and reducing the frequency of faults.

The value proposition of the Phase II technology lies in its advanced, yet accessible AI-powered solutions designed to maximize operational efficiency, enhance product quality, and reduce time-to-market. Through automated data analysis, minimal dependency on labeled data, enhanced anomaly understanding, and user-friendly interfaces, AutoEdge offers an ideal tool for businesses looking to optimize their quality assurance processes and leverage data-driven insights effectively.

3.2 Pricing and Validation

Our **revenue model** is strategically built around **two core components**. Initially, we levy an $80k *non-recurring engineering fee* per contract. This fee covers the cost of initial setup, integration, and personalizing our solution to align with each client's specific requirements. Subsequently, we introduce a $2,000 *per seat subscription fee*, fostering a steady revenue stream that evolves in correlation with our customers' growth. This fee includes regular updates, support, and maintenance. Not only does this business model promote *long-term partnerships and customer loyalty*, but it also simplifies budgeting and cost management for our clients.

In terms of pricing validation, we have **numerous case studies** that showcase the tangible benefits of AutoEdge. For instance, *American Innovations* experienced a significant improvement in defect detection in pipeline corrosion assessments, thanks to our large time-series model. This resulted in cutting assessment times from 3 days to 2 days, with considerable reductions in missed assessments, leading to *weekly savings of up to $3,000*.

Furthermore, our collaboration with *Sakaiya* led to substantial enhancements in their car dashboard manufacturing process. The integration of our anomaly detection system decreased the number of defective parts to less than 1%, significantly improving their quality control process. Additionally, it allowed a reduction in the size of the inspection team, generating *savings of over $100,000 annually*.

Finally, *Daikin* reaped the benefits of AutoEdge when they integrated it into their equipment performance metrics analysis. Our large time-series model provided comprehensive insights, enabling faster root cause analysis. The workload involved in anomaly detection was reduced from 18 hours to under 30 minutes, thus increasing overall efficiency. The financial impact was substantial, with each accurately detected anomaly leading to *savings of over $2,100*, thereby significantly optimizing cost management. These real-world applications validate the value and pricing of our solution. A detailed cost and assumptions analysis is presented in the section 4.4.

3.3 Competition and Market Position

Existing Competitors. As elaborated in section 1.2, apart from well-known solutions like Google's Visual Inspection AI and Microsoft Azure's Anomaly Detector, our comprehensive market research has spotlighted additional key players in AI-powered intelligent data solutions, or "Chat-GPT for data." This list includes **Tableau** [10], **DataRobot** [11], **Anodot** [12], and **Landing AI** [13]. Concurrently, promising startups such as **Seek** [14], **Olli** [15], **Baselit** [16], and **Defog** [17] are emerging, with the objective to democratize data access for non-specialists. These organizations specialize in distinct areas: Computer Vision (Google's Visual Inspection AI, Tableau, Landing AI), Anomaly Detection (Microsoft Azure's Anomaly Detector, DataRobot), and Chat-based Solutions (Seek, Olli, Baselit, Defog). Table 2 presents a comparison analysis.

Shortcomings. Despite their market presence, we've identified three significant shortcomings in their offerings: **#1: Lack of a robust open-source community.** Except for Tableau, the other competitors do not maintain a strong open-source community. In contrast, AutoEdge supports AutoKeras and TODS, boasting 240K impressions a month and approximately 12K active users. This vibrant community serves as a testament to our dedication to open-source and provides us with valuable feedback and innovations. **#2: Limited Explainable AI.** Many competitors lack a robust Explainable AI capability, which is crucial for understanding and trusting AI models. Without this feature, the decision-making process of AI models remains opaque to users, posing

Feature	AutoEdge	Visual-based	Anomaly Detector-based	Chat-based
Defect Detection	Visual + time-series	Visual inspection	Time-series	Time-series
Open-Source Support	Strong	Lacks strong open-source community	Lacks strong open-source community	Not supported
Pre-Labeled Data	Minimal pre-labeled data required	Requires pre-labeled data	Not supported	Limited
Time-Series Data	Tailored to handle time-series data	Insufficient proficiency	Excels at time-series anomaly detection	Supported
Automated Visual Inspection	Focused for medium-sized manufacturers	Focused on large companies	Not supported	Not supported
User-Friendly	Designed to be user-friendly	IT setup can pose challenges	Technical complexity can pose challenges	Yes
Integration	Seamless and quick integration	Complex	Complex and time-consuming	May be complex

Table 2: Comparing features of competitors, and AutoEdge

a challenge for adoption in many industries. In contrast, AutoEdge prioritizes Explainable AI, ensuring that our users can understand and trust the AI models they use. **#3: Not tailored for time-series data.** Most competitors' solutions are not specifically designed to handle time-series data effectively. Time-series data, ubiquitous in many industries, requires specific methods for efficient and accurate analysis. AutoEdge, however, is purpose-built to handle time-series data, providing sophisticated analysis capabilities and enabling more accurate insights and predictions.

3.4 Competitive Landscape

The competitive landscape of AI-powered intelligent data solutions is rapidly evolving and highly dynamic. Numerous companies are entering the market, each offering their unique set of products and services. These solutions leverage artificial intelligence and advanced analytics techniques to extract valuable insights from vast amounts of data, enabling organizations to make data-driven decisions and gain a competitive edge.

The competitive landscape can be categorized into several key players, including: **(1) Established Tech Giants**: Companies like Google, Microsoft, IBM, and Amazon Web Services (AWS) have significant market presence and offer comprehensive AI-powered data solutions. They provide cloud platforms, machine learning frameworks, and a range of data analytics tools for businesses of all sizes. **(2) Specialized AI Solution Providers**: Many companies focus exclusively on developing AI-powered data solutions. These include firms like DataRobot and Databricks. They offer platforms and tools that help organizations manage and analyze complex data sets efficiently. **(3) Traditional Analytics Providers**: Traditional analytics companies such as Tableau have also adapted to the AI-driven landscape. They have incorporated AI capabilities into their existing analytics platforms, enabling users to leverage machine learning algorithms for advanced insights. **(4) Startups and Scale-ups**: The AI space is witnessing a surge of startups and scale-ups that are disrupting the market with innovative approaches to intelligent data solutions. These companies focus on niche areas such as natural language processing, predictive analytics, computer vision, and anomaly detection. Examples include Seek, Olli, Baselit, and Defog. **(5) Industry-Specific Solutions**: Some companies provide AI-powered data solutions tailored to specific industries, such as healthcare, finance, retail, and manufacturing. These solutions address industry-specific challenges and compliance requirements, offering targeted insights and predictive analytics. Examples include Tempus (healthcare), Quantexa (financial crime detection), and Uptake (industrial IoT). **(6) Open-Source Communities**: Open-source communities play a crucial role in the development of AI-powered data solutions. Projects like TensorFlow, PyTorch, and Apache Spark have gained significant popularity and are widely adopted by companies to build their AI infrastructure.

3.5 Intellectual Property

Biannual legal counsel is sought from our dedicated legal team, to ensure our technology remains protected. As a tech-forward company, we've always been cognizant of the importance of securing our unique capabilities, which has led us to file multiple patents with the United States Patent and Trademark Office (USPTO).

(1) **Patent#1**: (US10560465B2 [18]) proposes a real-time anomaly detection approach for uni-modal time-series data stream. In contrast, our project focuses on manufacturing sensor data which are multi-modal time-series data streams and proposes to detect anomalies across all sensors. (2) **Patent#2**: (US10223635B2 [19]) proposes a model compression approach for deep neural network by replacing one layer in the neural network with compressed layers to produce the compressed network. In contrast, our project proposes a hardware-aware to automated machine learning (AutoML) technique which compresses deep neural network tailored to the target IoT hardware in an automated manner. (3) **Patent Application#3**: (US20160291552A1 [20]) proposes a system for rule management, predictive maintenance, and quality assurance that isn't flexible for the diverse challenges in manufacturing In summary, to the best of our knowledge, no existing IP blocks the commercialization of our proposed technology.

Our forward-looking IP strategy is driven by our commitment to innovation. We intend to protect our IP assets aggressively, filing for patent protection for any new features or processes we develop. Our timeline for patent submissions aligns with our product development milestones. Regular consultations with our legal counsel will be maintained, ensuring we are promptly adapting to any changes in the IP landscape.

4 Finance and Revenue Model

4.1 Staged Finance Plan

In Phase 1, already funded by $277k from SBIR and $300k from venture capital in March 2022, we entirely devoted our resources to R&D. Our key milestones here included customer discovery, prototype development, and filing preliminary patent applications to secure our intellectual property rights. The phase was instrumental in setting the foundation for AutoEdge.

Moving forward to Phase 2, we are requesting $1M from the SBIR program, and an additional 2M from venture capital in May 2024. The fund allocation here is 80% for R&D and 20% for expanding our sales force. During this phase, we focused on refining our minimum viable product (MVP), customizing it for each customer to reduce points of contact. In terms of intellectual property, we worked on strengthening our patent portfolio and safeguarding our unique technologies. We also initiated discussions with potential manufacturing partners during this phase to prepare for larger-scale production.

Milestone	**Timeframe**	**Financing Approach**	**Anticipaed Funding**
Customer discovery, Prototype development, Preliminary patent applications	Phase 1	SBIR Grant, Additional Funding, Venture Capital	$577k
Refine MVP, Customize for each customer, Strengthen patent portfolio, Initiate manufacturing partnerships	Phase 2	SBIR Grant, Additional Funding, Venture Capital, and Phase 2B ($500k)	$3M
Scale AutoEdge, Full-scale marketing campaign, Finalize manufacturing partnerships, Continual IP assessment	Phase 3 (Q4 2026)	Planned Funding Round	$12M

Looking ahead, Phase 3 is planned for Q4 of 2026, where we aim to raise $12M. The allocation includes 40% for continued R&D, 30% for expanding our sales force and customer support, and

30% for a robust marketing campaign. At this stage, our key technical milestone is to scale our product AutoEdge, enhancing its capabilities to handle larger data volumes and more complex operations. On the marketing front, we plan to launch a full-scale marketing campaign to increase product awareness and market penetration. In terms of manufacturing, we aim to finalize our manufacturing partners and begin mass production of AutoEdge. We also plan to maintain our focus on intellectual property by continually assessing the market for any potential IP acquisition opportunities to bolster our position and competitiveness.

4.2 Accessing Funds

AI POW LLC has a robust and extensive network of investors, partners, and customers. As an early-stage company, we have successfully raised a pre-seed round of $300k in March 2022 via a SAFE note with no cap and no discount. AI POW has launched its seed round in April 2023, aiming to raise a total of $3M with $2M from venture capital and an additional $1M from the NSF.

Our lead investor for this round is NetMind AI, a UK-based venture capital firm. As a testament to our solid relationship, NetMind AI is following up on their previous $300,000 pre-seed investment with a confirmed follow-up investment commitment. This highlights their confidence in our vision, team, and the technology we are developing. Quoting NetMind AI investor: *"Our interest in AI POW LLC extends beyond mere financial considerations, with us keenly looking forward to joining them in the next phase of their journey during the seed funding round."* (Letter of support 4. Mr. Yu Cheng, Chief Research Office. **NetMind**.)

Importantly, our customers have already started to contribute to our recurring revenue. We forecast an Annual Recurring Revenue (ARR) of $100,000 by the end of Phase II, illustrating our capability to generate consistent revenue and indicating the market's positive reception for AutoEdge. Also, our partnerships, previous funding history, and the recurring revenue from our existing customers lay a strong foundation for AI POW LLC's future growth and success. We are optimistic about our progress and the potential to disrupt the market with AutoEdge.

4.3 Projected Revenue Streams

AI POW LLC has adopted a Software-as-a-Service (SaaS) business model. Our commercialization plan has projected the following revenue streams:

In **Phase I (Year 2023)**, our revenue will mainly stem from two sources: non-recurring engineering (NRE) fees and unit sales. For each contract, we charge an NRE fee of $80k that covers the initial setup, integration, and customization of our AI solution to suit the specific needs of each customer. Additionally, we forecast revenue from the unit sales of our Mesa board, a crucial component of our AI solution. We aim to sell 25 licenses in 2023, which, at $2,000 per unit sold for replicating models, generates an **Annual Recurring Revenue (ARR) of $50k**.

As we transition to **Phase II (Year 2024)**, our business model will evolve our subscription-based recurring revenue source. This has established a consistent revenue stream that expands in tandem with our customers' growth. In this model, customers pay a recurring fee for access to our machine learning models that capture and preprocess data, are retrained on new datasets, and then redeployed for improved performance. Our projected timeline for initial revenues is based on current customer contracts and the sale of subscriptions to our AutoEdge platform. As we embrace a subscription model in 2024 and widen our customer base, we anticipate a substantial **ramp-up in our revenue**.

Reaching break-even operations depends on numerous variables, including costs related to research and development, sales, marketing, and personnel, among others. Our current financial projections indicate that we need to acquire a substantial number of users to attain this break-even point. With an average rate of new customer acquisition, we anticipate achieving this goal in 2027, as seen in our Pro Forma Income Statement However, it's essential to bear in mind that this is a basic calculation and doesn't account for possible changes in costs, pricing, or customer acquisition rate over time. We will remain vigilant of our financial status and operational costs, ready to modify our business model and strategies as needed to achieve break-even operations within a reasonable timeframe.

4.4 Pro Forma

From this pro forma income statement, we project that AI POW LLC will reach consistent profitability in the year 2027 when we expect to start earning a positive net income on two consecutive years. We expect the sale of units to increase linearly each year, beginning from 120 units sold in 2024 and ending with 5,500 units in 2028. We also assume a constant selling price per unit of $2,000 throughout all the years.

Early assumptions

1. New product sales Unit sales will grow linearly each year, beginning with 120 subscriptions sold in 2023 and ending with 5,500 subscriptions in 2028 facilitated by the Phase II work which supports product and process engineering needed for scale up. We also assume a constant selling price per unit of $2,000 throughout all the years.

2. Server Costs: IT costs, primarily based on our usage of cloud services such as Amazon Web Services (AWS), are estimated to be around $5,000 yearly. This variable cost will rise with the increased number of users, at a rate of $500 per ten users.

3. Engineering Installation Cost post sale Our personnel costs are based on maintaining a team of software engineers, with each engineer's annual salary being around $120,920. This team is expected to double each year.

4. Customer Support and Account Mgmt For the first three years, the estimated cost for maintaining a Level 3 Customer Care team, will be outsourced and is expected to cost 2% of new product sales. By the year 2027, we expect to have an in-house team with a yearly salary of $50,000 per employee and $12,000 for training and upskilling.

5. SBIR (Direct & Indirect), and Internal R&D: Annual R&D to keep the product competitive and to incorporate customer requests for enhancing customer loyalty: the yearly cost for Research and Development is based on maintaining a team of one to ten professionals with an average salary of $100,000 each. Additional resources and tools amount to about 20% of the personnel costs. Therefore, the estimated annual cost for R&D activities ranges from $120,000 to $1,200,000.

6. Sales expenses The annual cost for Business Development/Sales Liaison with partners, which includes a team of two professionals with salaries of $80,000 each and additional resources for travel, meetings, and partner liaison activities, amounts to approximately $180,000. We will hire an additional person by 2026 and keep increasing the team yearly.

7. Marketing expenses: Marketing is a fundamental aspect of our business strategy. For a Software as a Service (SaaS) company like us, we estimate an annual marketing cost of $100,000. This figure is an assumption based on the typical expenses of similar companies and might fluctuate based on the specifics of our marketing strategy.

8. Administrative (G&A): We expect to have significant G&A expenses in 2026 to cover our accounting fees, software costs for project management, and other related overhead costs.

9. Facilities: Our operations also require a physical workspace for our team. The going rate for office space in Houston is $33.34 per square foot annually. Given that each of our employees should have an average of 150 square feet, this results in a cost of $5,000 per employee per year.

Our team is expected to raise a 2 million seed round in 2024 with a stretch goal of $4 million.

Pro Forma Income Statement

Phase II AutoEdge
Auto Edge TM - US Market

AI POW LLC
For years 2024 to 2028

Market	Phase II (2024)	Phase II (2025)	2026	2027	2028
Served Available Market size	$ 107,799,389	$ 157,710,506	$ 230,730,471	$ 337,558,679	$ 493,848,347
Market Growth Rate	46%	46%	46%	46%	46%
Revenue					
Licenses/Subscriptions expected to be sold	120	350	720	1,550	5,500
$ avg selling price of total product	$ 2,000	$ 2,000	$ 2,000	$ 2,000	$ 2,000
New product sales	$ 240,000	$ 700,000	$ 1,440,000	$ 3,100,000	$ 11,000,000
Consulting or aftersale services	$ 24,000	$ 70,000	$ 144,000	$ 310,000	$ 1,100,000
Total Production sales (Revenue)	$264,000	$770,000	$1,584,000	$3,410,000	$12,100,000
% market share - total market	0.2%	0.5%	0.7%	1.0%	2.5%
SBIR/STTR Contract R&D	$ 475,000	$ 475,000	$ -	$ -	$ -
TABA Services	$ 25,000	$ 25,000	$ -	$ -	$ -
Total revenue	**$ 764,000**	**$ 1,270,000**	**$ 1,584,000**	**$ 3,410,000**	**$ 12,100,000**
Cost of Goods Sold					
Server Costs	$ 11,000	$ 22,500	$ 41,000	$ 82,500	$ 280,000
Engineering Installation Cost post sale	$ 120,920	$ 241,840	$ 483,680	$ 967,360	$ 1,934,720
Customer Support and Account Mgmt	$ 4,800	$ 14,000	$ 28,800	$ 62,000	$ 220,000
Other Incremental Expenses	$ -	$ -	$ -	$ -	$ -
Total COGS new product	$136,720	$278,340	$553,480	$1,111,860	$2,434,720
COGS (per unit)	$ 1,139	$ 795	$ 769	$ 717	$ 443
COGS consulting or after sale service	$ 12,000	$ 35,000	$ 72,000	$ 155,000	$ 550,000
Total COGS	$ 148,720	$ 313,340	$ 625,480	$ 1,266,860	$ 2,984,720
Gross Margin					
Total GM$	$ 615,280	$ 956,660	$ 958,520	$ 2,143,140	$ 9,115,280
Total Gross Margin %	81%	75%	61%	63%	75%
Operating Expenses					
SBIR & TABA Expenses (Direct & Indirect)	$ 454,545	$ 454,545	$ -	$ -	$ -
Sales	$ 180,000	$ 180,000	$ 360,000	$ 1,000,000	$ 2,000,000
Marketing	$ 100,000	$ 100,000	$ 100,000	$ 100,000	$ 100,000
Administrative (G&A)			$ 140,000	$ 140,000	$ 200,000
Legal	$ 15,000	$ 15,000	$ 15,000	$ 30,000	$ 30,000
Facilities	$ 10,000	$ 15,000	$ 30,000	$ 60,000	$ 100,000
Total Selling General and Administrative	$305,000	$310,000	$645,000	$1,330,000	$2,430,000
Internal R&D			$ 600,000	$ 750,000	$ 1,200,000
Total Operating Expenses	$ 759,545	$ 764,545	$ 1,245,000	$ 2,080,000	$ 3,630,000
EBITDA	$ (144,265)	$ 192,115	$ (286,480)	$ 63,140	$ 5,485,280
EBITDA Margin % (operating margin)	-18.9%	15.1%	-18.1%	1.9%	45.3%
Cash Proxy					
EBITDA	$ (144,265)	$ 192,115	$ (286,480)	$ 63,140	$ 5,485,280
+ Matching Grants			$ 500,000		
- Capital Expenditures					
- Loan Payments					
+ Investments (Paid in Capital)	$ 2,000,000				
Net Addition (Subtraction) from Cash	$ 1,855,735	$ 192,115	$ 213,520	$ 63,140	$ 5,485,280
Year-End Cash Proxy	**$ 1,855,735**	**$ 2,047,849**	**$ 2,261,369**	**$ 2,324,509**	**$ 7,809,789**

References of the commercialization plan

[1] Daikin North America. Daikin. Accessed: 2023-05-26.

[2] Sakaiya. Sakaiya company overview, Year. Accessed: 2023-05-26.

[3] American Innovations. American innovations company overview, Year. Accessed: 2023-05-26.

[4] Google Solutions. Google visual inspection ai. Accessed: 2023-05-26.

[5] Microsoft Services. Microsoft's azure anomaly detector. Accessed: 2023-05-26.

[6] MarketsandMarkets. Automated machine learning (automl) market, May 2023.

[7] Industry Week. Manufacturing technology show. Accessed: 2023-05-26.

[8] Manufacturing Summit. American manufacturing summit. Accessed: 2023-05-26.

[9] NetMindAI. Netmindai. Accessed: 2023-05-26.

[10] Pitchbook Company Profile. Tableau, (Accessed May 26, 2023). https://my.pitchbook.com/profile/44506-99/company/profile.

[11] Pitchbook Company Profile. DataRobot, (Accessed May 26, 2023). https://my.pitchbook.com/profile/57523-60/company/profile.

[12] Pitchbook Company Profile. Anodot, (Accessed May 26, 2023). https://my.pitchbook.com/profile/120215-71/company/profile.

[13] Pitchbook Company Profile. LandingAI, (Accessed May 26, 2023). https://my.pitchbook.com/profile/224101-18/company/profile.

[14] Pitchbook Company Profile. Seek AI, (Accessed May 26, 2023). https://my.pitchbook.com/profile/491754-16/company/profile.

[15] Pitchbook Company Profile. Olli, (Accessed May 26, 2023). https://my.pitchbook.com/profile/515917-81/company/profile.

[16] Pitchbook Company Profile. Baselit, (Accessed May 26, 2023). https://my.pitchbook.com/profile/520700-14/company/profile.

[17] Pitchbook Company Profile. Defog, (Accessed May 26, 2023). https://my.pitchbook.com/profile/520663-60/company/profile.

[18] Gaurav D. Ghare and Roger Shane Barga. Real time anomaly detection for data streams. US10560465B2, 2016.

[19] Venkata Sreekanta Reddy ANNAPUREDDY, Daniel Hendricus Franciscus DIJKMAN, and David Jonathan Julian. Real time anomaly detection for data streams. US20160217369A1, 2015.

[20] Biplab Pal, Avijit Sarkar, Neeraj Nagi, and Prosenjit Pal. System for rule management, predictive maintenance and quality assurance of a process and machine using reconfigurable sensor networks and big data machine learning. US20160291552A1, 2015.