ICCGI 2023

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ICCGI 2023

Forward

The Eighteenth International Multi-Conference on Computing in the Global Information Technology (ICCGI 2023), held between March 13th and March 17th, 2023, continued a series of events covering a large spectrum of topics related to global knowledge concerning computation, technologies, mechanisms, cognitive patterns, thinking, communications, user-centric approaches, nanotechnologies, and advanced networking and systems. The conference topics focused on challenging aspects in the next generation of information technology and communications related to the computing paradigms (mobile computing, database computing, GRID computing, multi-agent computing, autonomic computing, evolutionary computation) and communication and networking and telecommunications technologies (mobility, networking, bio-technologies, autonomous systems, image processing, Internet and web technologies), towards secure, self-defendable, autonomous, privacy-safe, and context-aware scalable systems.

This conference intended to expose the scientists to the latest developments covering a variety of complementary topics, aiming to enhance one's understanding of the overall picture of computing in the global information technology.

We take here the opportunity to warmly thank all the members of the ICCGI 2023 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to ICCGI 2023. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the ICCGI 2023 organizing committee for their help in handling the logistics of this event.

We hope that ICCGI 2023 was a successful international forum for the exchange of ideas and results between academia and industry and for the promotion of progress in the field of computing and global information technology.

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Smart Call Routing Utilizing a Multi-Agent Architecture

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***Abstract*— We present an agent-based architecture for routing incoming calls based on user needs and provider skill levels. We illustrate the use of the architecture in the context of routing Information Technology (IT) help desk incoming calls. The presented architecture reduces the need for involving clients in multiple iterations of assessment of their reported issues before a resolution is reached.**

Keywords - agents; decision-support; human-computer collaboration.

I. Introduction

Traditionally, corporate computing systems consisted of hardware and software systems purchased from one or more vendors and maintained on site typically by local information technology staff. In recent years, a gradual shift occurred to a managed system model where corporations contract a vendor to install and support integrated IT systems [1]. This shift was accompanied by a shift of the help desk support from the corporate IT department to the vendor's own staff. As a result, vendors set up large help desk installations where staff accept calls from personnel at a large number of corporate clients and attempt to troubleshoot a variety of issues [2]. Because of the diverse needs of the different clients and even the diverse issues that face each client, help desk personnel are trained to quickly attempt to identify the type of problem and route it to the appropriate staff for further evaluation. This process is often plagued with inefficiency with the same call often rerouted to multiple human agents, resulting in a high level of user frustration. In this paper, we present a multi-agent approach to automate the process of routing the call to the most appropriate human agent for the problem presented. Each computerized agent specializes in one type of problems corresponding to the expertise of a human staff technician and is tasked with identifying whether the problem presented falls within the scope of its area of specialty and thus routing the call to the associated staff technician. The goal of this process is to minimize the number of technicians a caller would interact with before their problem is solved. Given the large number of possible issues, a large number of agents is necessary. This paper presents a partial solution involving a subset of the needed agents. Section II of this paper describes the nature of the problem in detail, Section III describes the proposed solution, and Section IV presents the results of our research and outlines our future efforts.

II. Nature of Help Desk Problems

As described above, the issues which have to be handled by help desk personnel span a very large range of problems, from hardware issues with diverse hardware architectures to software issues with a large number of software applications. This problem is often complicated by the fact that most corporate users who often call for help are non-technical staff without the necessary background to determine the nature of any issues they might be encountering. As a result, symptoms communicated to help desk staff are often vague and incomplete [2]. Due to the typically large number of calls at a typical call center, help desk personnel are often under pressure to handle the call by routing it to the appropriate troubleshooting personnel as fast as possible. Combined with the fact that the first line of help desk personnel is often the technicians with the least experience, this frequently results in calls routed to the wrong troubleshooting technicians who would then return the call to the intake staff for re-assessment. Clients report (in the post-service surveys collected by our corporate client) that this process is often repeated multiple times resulting in high levels of dissatisfaction. Figure 1 shows the flow of a typical client call. From this diagram, we can see that there are multiple paths for reevaluation that can result in the same problem being evaluated many times, resulting in high levels of client dissatisfaction. This process is further complicated by having the entire help desk often located in a foreign country with help desk staff for whom English is not the first language, resulting in even higher levels of dissatisfaction among clients. Frequently, help desks in different countries are utilized to allow for round the clock staffing, which often results in inconsistent response based on the level of skill and training at the different centers.

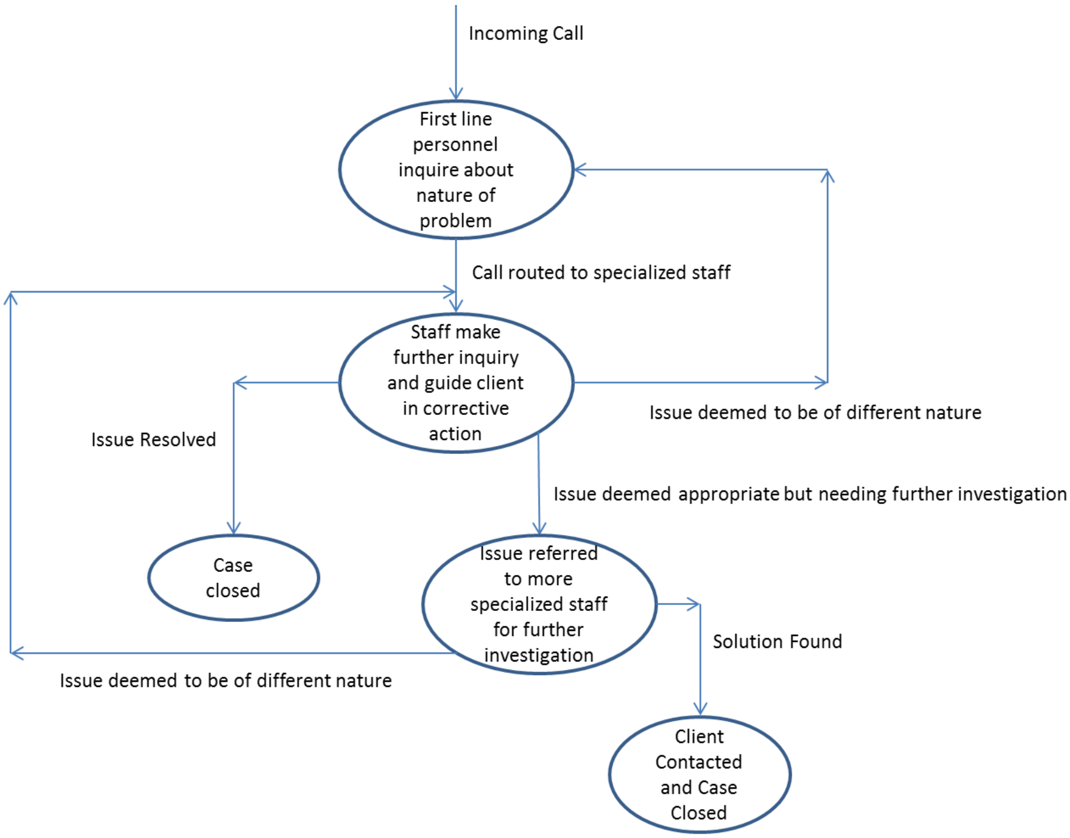

Figure 1. Original Flow of Client Incoming Call.

III. AGENT BASED SOLUTION

We were presented with this problem by the manager of a call system for a major solution provider (A confidentiality agreement prevents the disclosure of the provider). We ran an analysis on the performance of the first line personnel in routing the calls and determined that the average call is routed back to the first line personnel an average of 5.6 iterations per call. Once the call is routed to even more specialized personnel, they are routed back to the first specialist an average of 1.7 iterations per call. By examining the data of a large number of historic calls, it was determined that the large number of repeated referrals is in many cases caused by the vague nature of the symptoms provided by the client. These vague symptoms make it possible for the cause of the issue to be one of many possibilities. Because of the large number of combinations of possibilities, a fully automated diagnostic system like these presented in [3] or [4] was deemed inappropriate. Additionally, a routing system based on fixed rules (similar to the manual referral system being replaced) was deemed too rigid. The manual system relied on over-simplified rules of the form "If the client is complaining about a slow response rate, refer the call to a hardware technician." Instead, we focused on developing a decision support system for the first line personnel to aid in the diagnostic process. The proposed solution is based on an agent architecture consisting of a large number of agents with each agent specializing in a narrowly focused problem. Each of these agents is based on diagnostic information obtained from past cases. This design is based on a similar architecture we have previously used in managing agricultural systems [5], [6] and in controlling unmanned air vehicles [7], [8]. Once the first-line technician obtains the symptoms of the impending issue from the client, the technician enters the data into the agent intake system. The agent intake system passes the data to all the agent systems. Each agent system runs its independent assessment of the data to determine whether its area of specialty might be the culprit. Each agent is based on a simple set of rules to determine a confidence factor in the problem area falling within its area of specialty. The rules are designed to first examine rules that would eliminate the possibility of the problem falling within the area of expertise of the particular

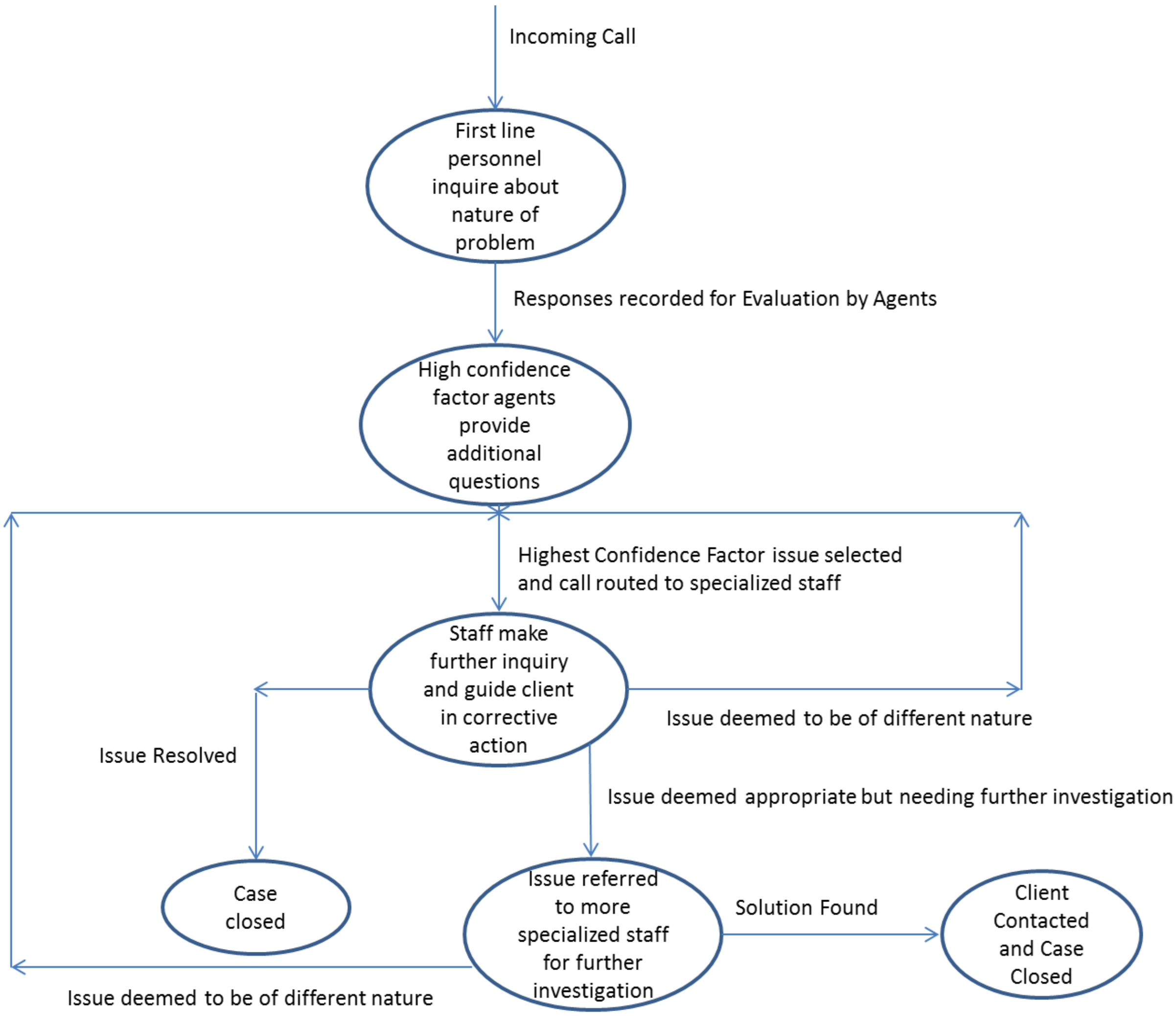

Figure 2. Agent-Based flow of Client Incoming Call.

agent in order to minimize the probability of needing to collect more data from the user. Agents returning confidence factors of 50% or higher are considered for further evaluation. Every agent within that group provides an additional set of questions (if needed) to the intake technician to ask the user. This step ensures that as much data as possible is collected from the client up-front, reducing the need for involving the client in multiple iterations of re-evaluation. Responses to these questions assist the agent in refining its confidence factors. After this assessment, any agent whose confidence factor drops below the 50% threshold is eliminated from further consideration. The specialty areas of the remaining agents are then sorted in descending order of confidence factors. The top area of specialty is then referred to the specialty team of technicians for further assessment. Only if the team of specialists deems the problem not to be of their specialty, is the problem referred to the next team of specialists. Figure 2 shows the flow of information under this solution. If no agents exceed the 50% threshold, the case is handled by the intake technician agents using the traditional methods used prior to the implementation of the agent system.

We implemented a prototype of this system using a limited number of agents. The initial prototype included 6 agents. Based on the encouraging initial results, we have been steadily expanding the number of agents, the system currently encompasses over 50 agents. In situations where the incoming calls fell within the area of specialty of the incoming agents, the number of iterations where additional data was needed from the client was significantly reduced and, in most cases, eliminated. The average number of referrals of each call back to in-take specialists dropped from an average of 5.6 iterations per call to 2.4 iterations per call. As a result, clients reported a much higher level of satisfaction as indicated by a voluntary client satisfaction survey that is administered to clients after completion of their calls. The same survey has always been used even before introducing the agent-system solution. These results are based on qualitative data. We are considering redesigning the survey to include numeric measures in the future.

IV. CONCLUSIONS

The limited prototype of the proposed architecture resulted in a higher level of satisfaction among clients whose problems fell within the scope of the implemented agents. Once the developed agents cover all existing systems, we expect the overall client's level of satisfaction to increase substantially. This type of system is never completed since new software and hardware systems are constantly being introduced, needing additional agents. We expect a delay between the introduction of any new system and the development of appropriate agents for that system. This delay is necessary for the accumulation of a sufficient number of cases to be used as the basis for the knowledge of the necessary agents.

Many solution providers utilize call centers in different countries to allow for call centers to be staffed around the clock. The availability of this agent system to the first-line technicians in all locations allows for a consistent performance among the different centers.

The developed architecture is flexible enough to support other areas of needed technical support through the customization of the knowledgebases for the different agents. We plan to test this architecture on other application areas in the future.

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Examining the Relationship of Digitalization on Business Performance: A Study from the Indian Manufacturing Sector

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Abstract— **The Indian manufacturing industry is undergoing a significant change after the global pandemic. The supply chain disruption from Covid-19 has forced many manufacturing industries to speed up the adoption of digitalization in their supply chain to address the growing need for convenience and more rapid "anytime anywhere" solutions. As a result, manufacturing industries are using advanced technology in their supply chain. Digitalization has the ability to drive the efficiency of their processes and reduce business cost. This study investigates the relationship between DIGitalization (DIG) and Business Performance (BP) in the Indian manufacturing sector. In this context, a scientific research model has been developed from the existing literature. The proposed model was tested using statistical data collected from Vice president/Associate Vice President/Divisional/Chief Managers/ Project Managers/ Senior Managers/ divisional Managers, IT managers, consultants, and project leaders of manufacturing industries. Data were analyzed through Structural Equation Modelling (SEM) using Analysis of Moment Structure (AMOS 22.0). Our empirical result indicates that there is a significant positive relationship between digitalization and business performance in the Indian manufacturing sector.**

Keywords - Digitalization; Business Performance and Structural Equation Modelling.

I. INTRODUCTION

The COVID-19 pandemic spread across the world affecting populations across countries [44]. The COVID-19 virus disrupted the Indian manufacturing sector due to the worldwide lockdown. Most manufacturing setups lack an end-to-end view of their supply chain such as end-to-end visibility, data-sharing across silos, real - time response capabilities, and flexibility in last-mile delivery. To address the above issues, the manufacturing industry can leverage digitalization with the use of Industry 4.0 technologies, to provide end-to-end supply chain management visibility. Digitalization results in increased operational efficiency and gross margin for businesses [25]. To achieve the above, the information must be shared between the manufacturing floor and business systems in real-time. Better integration of data and processes and real-time capturing of data from the machine and shop floor will enable manufacturing organizations to fine-tune their operations and produce products according to the demand of customers. In digitalization, firms implement a broad set of new technologies to optimize their business processes to improve operational efficiency and speed.

Indian manufacturing companies are on a secular growth trend due to their correlation with the growing Indian economy, which is characterized by rising demand in the domestic market and worldwide growth opportunities. According to India Brand Equity Foundation (IBEF), "By the year 2030, India has the potential to become a global manufacturing hub and it can add more than US $500 billion annually to the global economy".

The digital transformation market size in manufacturing has been valued at USD 263.93 billion and it is poised to reach USD 767.82 billion by 2026 with a CAGR of 19.48% during the forecast period 2021-2026 [32]. This digital transformation enables increased visibility, control and optimisation of production processes by integrating operations technology with information technology. The goal of value chain management is to improve bottom line of business by improving operational efficiency while preserving product quality while lowering inventory carrying costs. This builds customer confidence and Customer satisfaction. When industrial processes are digitalized, mistakes caused by lost or misread data are eliminated which is prevalent in manual operations.

Based on the above insight, current literature on digitalization does not empirically demonstrate a relationship between digitalization and business performance. Thus, we formulated our research questions to address these gaps in knowledge. Our study aims to empirically examine the relationship between digitalization and business performance in the Indian manufacturing sector. The following research question has been identified in our study.

RQ1. Does digitalization have a positive relationship with business performance in the Indian manufacturing sector?

To answer the above question, a conceptual model was developed to analyze the relationship between digitalization and business performance and the model was tested statistically through SEM (AMOS 22.0 software).

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The organization of the paper is as follows. Section II provides the literature review, Section III explains the model conceptualization, Section IV describes the research methods, and Section V presents the analysis and results, followed by results discussion, conclusion, limitations, and further direction of research.

II. LITERATURE SURVEY

A. *Digitalization*

The 'digitalisation of manufacturing' has recently become one of the most prominent themes for major economies [3][17][33][41]. "Digitization" and "Digitalization" are two constitutive definitions that were used interchangeably in the academic literature [33][41]. At a fundamental level, digitization creates excellent sources of data, and can be defined as "moving from analogue to digital data for streamlining existing processes" [33][41]. "Digitalization is defined as adopting digital technologies to facilitate business operations" [2][13]. Digitalization is a process that takes advantage of cutting-edge digital technologies in order to enhance productivity and improve operational efficiency cutting-edge technology like Artificial Intelligence (AI), Virtual Reality (VR) and Augmented Reality (AR), Internet of Things (IoT), Cloud computing, and robotics are driving growth of manufacturing industries [51]. According to Gobble, “Digitalization is the use of digital technology, digital information, and other resources to create value in new ways" [11]. According to Gartner, "Digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities" [10]. According to Westerman et al., “digital transformation is the use of technology to radically improve the performance or reach of enterprises" [50]. In a nutshell, digitization refers to information, while digitalization refers to processes. Lenka et al. explained that "Digitalization enables the processes, resources interactions and outcome between manufacturing firms and the customer to co-create value at the new frontiers of the business" [29]. According to Agarwal and Narain, the following are potential benefits of digitalization: "greater transparency", "reduced inventory levels", "clear visibility of inventory", "more decentralized warehousing", "delivery times reduction", "a better understanding of customer's requirements", "higher sales and profit margins", "improved supply chain flexibility", "better decision-making processes" and "maintaining competitive advantages" [1]. Big data analytics and cloud-based systems in the context of Industry 4.0 can significantly improve operational efficiencies [30][34][42][48]. The study has established factors to measure the perceived benefits of implementing Industry 4.0 technology [16]. Digitalization has the ability to improve flexibility, agility, and responsiveness as per customer demand in dynamic market conditions [37]. Implementing digitization in manufacturing gives an instant boost to productivity and allows quick project execution so manufacturers can meet aggressive deadlines. With digitalization, manufacturers can share real-time data across the globe also data can have accessed by anyone from anywhere [5].

B. *Business performance*

Business performance measures the actual performance of a business against intended goals. Regular review of the business performance saves the business against any financial or organizational problems and helps the businesses lower operational costs and improve productivity [7].Any organizational initiative, including supply chain management, should ultimately lead to enhanced organizational performance. Numerous authors have measured business performance by utilizing "financial and market indicators" such as "market share", "return on investment", "the profit margin on sales", "overall competitive position", and "the growth of market share", "sales and return on investment" [39][45][47][49][52][53].

C. *Digitalization and business performance*

Various studies have proved the significant relationship of technology adoption with business performance [4][12]. Digitalization increases revenue for the organization's stakeholders by widening the distribution of sales channels and increasing the productivity of industrial processes by reducing operational expenses or shortening the duration of operations. According to Horváth and Szerb, “Digital management practices with the use of IT tools tend to enhance business performance” [21]. Implementation of Big data is related to this concept, and its impact on business performance has been shown [9]. According to Hensher, leveraging digital platforms can reduce operational costs in turn its leads to business performance [18]. There is a significant positive effect of strategy or technology implementation from Industry 4.0 on business performance among SMEs [35]. It is also proven that Industry 4.0 technologies have a positive influence on service, and production and they enhance business performance [24][35][43]. Continuous innovation in technology can strengthen the relationship between people, processes, and performance [38]. According to [15], the use of digital technology has a positive relationship with business performance. According to reference [27], there is a positive relationship between blockchain technology, Supply Chain Integration (SCI) and Sustainable Supply Chain Performance (SSCP).

III. MODEL CONCEPTUALIZATION

Based on the deep understanding of research questions from the obtainable literature and experts' insights we developed a conceptual model that analyses the relationship between digitalization and business performance. As an illustration, Figure 1 shows the hypothesized model which sheds light on the relationship between digitalization and business performance. 'Digitalization' is conceptualized as a five first order construct adapted from [19][46][54], whereas business performance of the manufacturing sectorwill be evaluated through "financial performance" and "market performance" [26][28]. Using literature support, the expected relationships between digitalization and business performance are discussed and hypothesis relating these variables are developed. Subsequently during our pilot study phase, the dimensions and items of digitalization and business performance were verified and validated using confirmatory factor analysis.

Hypothesis: There is a significant relationship between digitalization and business performance in Indian manufacturing sector.

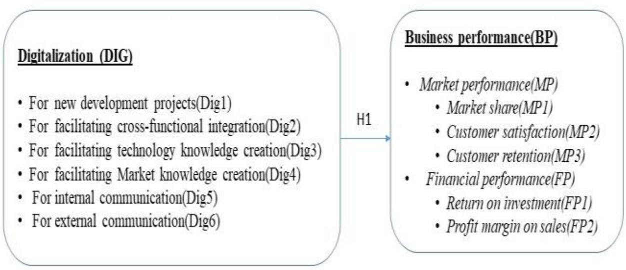

Figure 1. A Conceptual research model and hypotheses.

IV. METHOD

The research uses a quantitative approach to examine the relationship of digitalization and business performance in the Indian manufacturing context. Literature review supplemented by expert advice acts as an input to develop a questionnaire as per the objectives of the research. This gave us extensive information about the constructs namely digitalization and business performance for Indian manufacturing industry. A preliminary questionnaire was drawn up (see Appendix A), post which pre-testing was performed on 50 respondents to evaluate the clear and comprehensible wording of the questionnaire.

Data was collected from Vice Presidents (VP), Associate Vice President (AVP), Deputy Vice President (DVP) senior managers, IT managers, consultants, and project leaders and asked to fill the questionnaire survey. Data collection occurred between third week of December 2021 to Forth week of October 2022. Out of 234 usable responses, the survey revealed that around 53% of respondents were between the ages of 25-35, 36.33% were between 35-50, and the other 10.68% were above 51 years old. Furthermore, 38.03% of participants were VP/AVP/DVP/Chief Managers/Project Managers/Senior Managers/Divisional Managers, 34.19% were Technology experts and consultants, 14.96% were Technology product/marketing Managers, and the remaining participants fell into other categories.

V. ANALYSIS AND RESULTS

A. *Preliminary analysis and measurement model*

A Confirmatory Factor Analysis (CFA) was used to investigate the internal construct reliability, convergent validity, and discriminant validity of measurement model. Statistical Package for the Social Sciences (SPSS 22.0) and AMOS 22.0 are used for empirical analysis. Table I shows the psychometric properties of the measurement model. The "Cronbach alpha" and "composite reliability" of all constructs were above the threshold of 0.70 which confirmed internal consistency reliability (presented in Table I).

TABLE I. RELIABILITY AND ITEMS LOADING OF THE MEASUREMENT MODEL

Construct	Items	Loading	Cronbach (α)	Composite reliability	Average variance extracted
Digitaliza-tion (DIG)	DIG1	0.879	0.921	0.938	0.719
	DIG2	0.760			
	DIG3	0.886			
	DIG4	0.876			
	DIG5	0.872			
	DIG6	0.805			
Business Perfor-mance (BP)	MP1	0.811	0.860	0.984	0.739
	MP2	0.896			
	MP3	0.915			
	FP1	0.835			
	FP2	0.837			

Hair et al. described that "Discriminant validity shows the extent to which a construct is truly distinct from other constructs" [20]. According to Fornell and Larcker, " the square root of the Average Variance Extracted (AVE) of each construct should be much larger than the correlation of the specific construct with any of the other constructs" [8]. The value of AVE for each construct should be at least 0.50. Table II demonstrates the square root of an AVE of any latent constructs is much larger than the correlation between them which confirm the discriminant validity [8]. It is evident from Table II that the questionnaire has a valid and reliable instrument for measurement of digitalization and business performance in manufacturing sector.

TABLE II : DISCRIMINANT VALIDITY OF THE MEASUREMENT MODEL

	DIG	BP
DIG	**0.874**	0.322
BP	0.322	**0.859**

Note: Diagonal in bold represents the square root of AVE whereas the off-diagonal represents correlations between constructs

To examine the "fit" of the measurement model, a number of model fit indices were obtained from the confirmatory factor analysis like Chi-square/df (Degree of freedom) = 2.953 CFI (Comparative Fit Index) = 0.959, GFI (Goodness of Fit Index) = 0.919, NFI (Normed Fit Index) = 0.939, TLI (Tucker-Lewis index) = 0.944 and Root Mean Square Error of Approximation (RMSEA) = 0.092. Gefen and Straub (2000) has proposed the acceptable fit of respective values of $\chi 2$/df, should be less than 5, GFI, CFI, TLI and NFI should be more then 0.9 and the RMSEA value must be lower than 1. Table III clearly demonstrates that measurement model posited goodness-of-fit indices indicating a good fit with the collected data so we can proceed further for testing the structural model using SEM.

TABLE III. SUMMARY OF GOODNESS-OF-FIT INDICES FOR MEASUREMENT MODEL

Model Fit Index	Chi-square/ Degree of freedom	CFI	GFI	NFI	TLI	RMSEA
Model	2.953	0.959	0.919	0.939	0.944	0.092

B. *Assessment of the structural model*

According to Hair, "A structural model is a conceptual representation of the hypothesized relationships between constructs" [20]. In order to examine the proposed model and relationships, the test of the structural model was performed on SPSS 26.0 and AMOS 22 using structural equation modeling. Table IV depicts the goodness-of-fit indices for the structural model: $\chi 2$/df, CFI, GFI, NFI, and TLI values are 2.953,0.959,0.919,0.939,0.944 The RMSEA shows a value of 0.092. Thus, we can conclude that the structural model is accepted as per goodness-of-fit indices. We can proceed to test a statistical hypothesis defined in the model.

TABLE IV. SUMMARY OF GOODNESS-OF-FIT INDICES FOR STRUCTURAL MODEL

Model Fit Index	Chi-square/ Degree of freedom	CFI	GFI	NFI	TLI	RMSEA
Model	2.953	0.959	0.919	0.939	0.944	0.092

Table V summarizes the standardized path coefficients (β), standard error and hypotheses result. The level of significance (α) is set at 0.05.

The result reveals that digitalization has a positive and significant relationship with business performance (β=0.322; $p < 0.05$), supporting the hypothesis. The result was consistent with theoretical expectations and the relationship is significant as the p-value is less than 0.05.

TABLE V : SUMMARY OF A HYPOTHESIS TEST

path	Estimates (β)	Unstandardized Regression Weight	S. E.	C. R.	P	Result support
BP<-DIG	0.322	0.233	.062	3.784	***	Yes

Notes: β = standardized beta coefficients, ***p<.005
S.E.= standard error
C. R. = Critical ratio
P = Estimated probability

VI. RESULT DISCUSSIONS

Digitalization is one of the biggest buzzwords across every business around the globe. Digitization is often joined by digitalisation and digital transformation in both conversations and business practices. The primary objective of this study to investigate the relationship of digitalization on business performance in Indian manufacturing sector. The conceptualized research model was build using existing literature, practical insights and consultation with the subject experts. The results of statistical testing of hypothesis reveals that digitalization has a positive relationship with business performance. Horváth and Szerb (2018) are line with the findings that management practices linked to digitalization and the use of digital tools increase business performance. Several studies have demonstrated that technology can improve business processes and boost performance [10][22][40]. IT has entered in an era of digitalisation where digital technologies can boost sustainable growth by spurring innovation and differentiation. By integrating digital technologies in current business processes, it allows authorized users to access the information more efficiently, quickly, intuitively and securely. Greater efficiencies and business benefits can boost profitability of the organization [36]. McKeown and Philip deliberated a business transformation to be "an overarching concept encompassing a range of competitive strategies which organizations adopt in order to bring about significant improvements in business performance" [31]. Our findings demonstrate that digitalization can significantly bolster business performance in industrial firms. It can do so by boosting efficiency, lessening expenses, optimizing quality, and offering new business prospects. However, to reap the rewards of digital advancements, we need thoughtful preparation, investment in the proper tools and infrastructure, and a thorough comprehension of the potential advantages and difficulties.

VII. CONCLUSION AND LIMITATIONS

Our study takes a first step towards examining the relationship between digitalization and business performance in the Indian manufacturing sector. From the empirical results, it was evidently specified that digitalization has a positive relationship with business performance.

This study has some limitations and opportunities for future research.The findings of our research primarily focus on the Indian manufacturing sector which does not provide an adequate basis for generalization. Moreover, the said limitation potentially paves the way for further research. For improving the generalization of the study, the model can be tested in other countries. Further research can be conducted to investigate the relationship between digitalization andsupply chain performance, competitive advantage, and organizational resilience.

APPENDIX A

Questionnaire

Measures of the Digitalization(Digital)

Source: adapted from [19][46][54]

Digitalization defines the use of digitization as a lever to achieve change in processes.Please circle the appropriate number that accurately the status of digitalization

1	2	3	4	5
Very little extent	little extent	some extent	great extent	Verygreat extent

DIG/Dig1	Digitalization for new product development projects
DIG/Dig2	Digitalization for facilitating cross-functional integration
DIG/Dig	Digitalization for facilitating technology knowledge creation
DIG/Dig4	Digitalization for facilitating market knowledge creation
DIG/Dig5	Digitalization for internal communication (e.g., across different departments, across different levels of the organization)
DIG/Dig6	Digitalization for external communication (e.g., suppliers, customers, channel members)"

Measures of the Business Performance (BP)

Source: adapted from [26][28]

In this section, we are trying to measure the Business Performance. Please mark the best estimate that accurately reflects the status of Business performance.

1	2	3	4	5
Very little extent	little extent	some extent	great extent	Very great extent

Financial Performance (FP)

BP/FP1	Return on investment
BP/FP2	Profit margin on sales

Market Performance (MP)

BP/MP1	Market Share
BP/MP2	Customer satisfaction
BP/MP3	Customer retention

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Weight Difference Propagation for Stochastic Gradient Descent Learning

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***Abstract*—This paper proposes a new stochastic (mini-batch) training algorithm to reduce the computational and hardware implementation costs of the error Back Propagation (BP) method. In recent years, with the rapid development of IoT, there has been an increasing necessity to use microcomputers, especially edge computers that implement neural networks capable of training large-scale data. Since the neural network training is based on the BP method, the error propagation architecture from the output to the input layers is required for each training sample to calculate the gradient. As a result, the hardware and computational costs are increased. This paper attempts to improve the BP method by using the inner product of the weights and their updated amounts (differences) for training reducing the hardware and computational costs. This method eliminates the requirement of the BP architecture for each training sample in mini-batch and calculates the amounts of the weight update with only one weight difference propagation. This means that the proposed method can reduce the computational complexity in the backward calculations of the training to $1/b$ (b is the mini-batch size) compared to BP. Computer simulations demonstrate the effectiveness of the proposed method.**

***Index Terms*—neural network, gradient-based training algorithm, stochastic gradient descent method, error back propagation, weight difference propagation**

I. Introduction

With the development of information and communication technology, various devices have been converted to IoT, making it possible to acquire and store diverse and vast amounts of data. The complexity (nonlinearity) of data and its volume increase day by day. Developing technologies can process large-scale nonlinear data with high accuracy and speed. In recent years, Artificial Intelligence (AI) has attracted attention as one of the technologies that make this possible and has been applied in various fields, including mechanical engineering, statistics, physics, economics, cognitive science, and brain science. The core technology in the rapid development of AI is neural networks (NNs) [1] [2]. NNs are generally trained using gradient algorithms based on the error Back Propagation (BP) method. BP training is an efficient and practical algorithm, and various improvement methods have been proposed. One of the improved methods is the Stochastic Gradient Descent (SGD) method for big data learning [1].

Recently, several training algorithms have been proposed considering biological plausibility [3]–[6]. These researches began with questions such as, "Does the biological brain perform complex and accurate backward calculations like BP?" [3] [6] or "Is it necessary to calculate the exact gradient used in training?" [4] [5]. Furthermore, a gradient-based training algorithm that does not require the backpropagation of errors has been proposed [7]–[9]. This algorithm can potentially reduce computational and hardware burdens even when processed by microcontrollers installed in IoT devices. However, these algorithms are unsuitable for asynchronous parallel learning or training large datasets and still need improvement. In addition, there are preliminary simulation experiments of the proposed algorithms, and the learning accuracy for recent nonlinear data is not guaranteed.

In this paper, focusing on the algorithm of [7]–[9], a novel algorithm is proposed to simplify the calculation of the gradient. The proposed method is referred to as Stochastic Weight Difference Propagation (SWDP) to improve the disadvantages of SGD. SWDP differs from the conventional SGD in that the weights can be updated by only the inner product of the post-synaptic weights and their differences. This enables parallel training of each neuron in each layer. Therefore, the backward process for each training sample in mini-batch (stochastic) training is unnecessary, and the hardware and computational cost can be reduced. This means that the proposed method can reduce the computational complexity in the backward calculations of the training to $1/b$ (b is the mini-batch size) compared to BP. The proposed method, compared with the conventional SGD method on two benchmark problems and simulations, demonstrates its effectiveness.

The paper is organized as follows: Section 2 describes the training of SGD. In Section 3, the proposed SWDP is derived and explained. In Section 4, the computational cost of SGD and SWDP is discussed. Sections 5 and 6 present computational simulations and conclusions, respectively.

II. Stochastic Gradient Descent method

This paper considers the multi-layer feed-forward NN training, which is an unconstrained optimization problem to minimize the error function $E(\mathbf{w})$ concerning the weight vector $\mathbf{w} \in \mathbb{R}^n$.

$$\min_{\mathbf{w}\in\mathbb{R}^n} \quad E(\mathbf{w}). \tag{1}$$

There are two training methods for error Back Propagation (BP): batch and stochastic (mini-batch) strategies. All training samples in a dataset T_r are used in an epoch to calculate

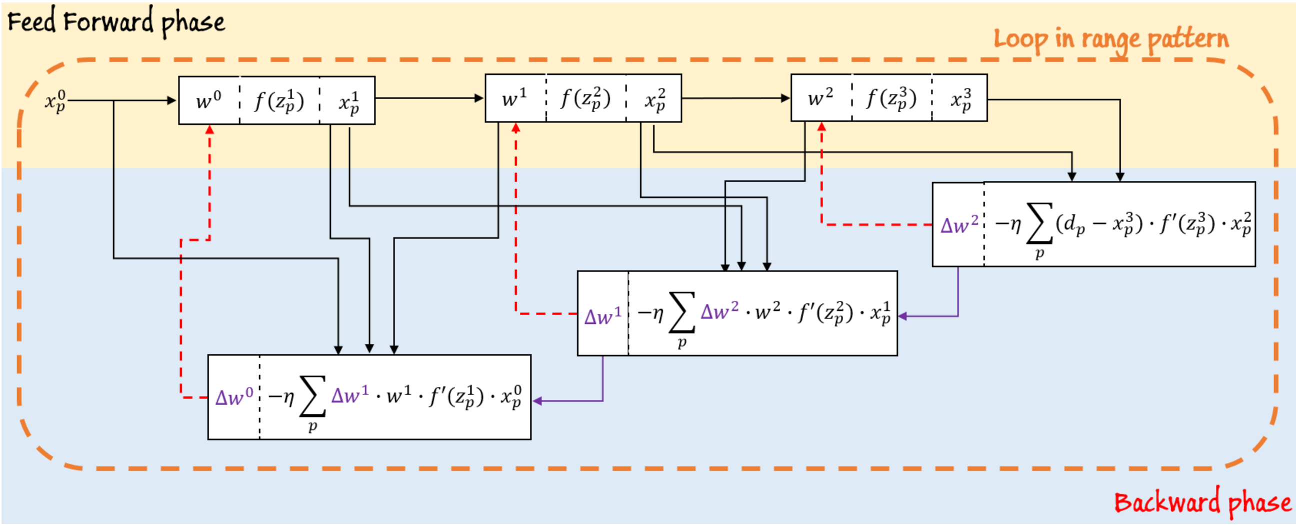

Fig. 1. Structural diagram of SGD.

gradients in the batch strategy. The error function $E(\mathbf{w})$ is defined as

$$E(\mathbf{w}) = \frac{1}{|T_r|} \sum_{p \in T_r} E_p(\mathbf{w}), \tag{2}$$

where, $|T_r|$ denotes the number of samples, and $E_p(\mathbf{w})$ is the error of the p^{th} sample. On the other hand, the stochastic training strategy in BP, so-call Stochastic Gradient Descent (SGD), uses $X \subseteq T_r$ dataset randomly selected from T_r in an iteration to calculate the gradient. The error function $E_b(\mathbf{w})$ of SGD is defined as

$$E_b(\mathbf{w}) = \frac{1}{b} \sum_{p \in X} E_p(\mathbf{w}), \tag{3}$$

where $b = |X|$ is the mini-batch size and if $X = T_r$ and $b = |T_r|$ then mini-batch training shifts to the batch mode.

Let $\mathbf{x}_p$ and $\mathbf{o}_p$ be the p^{th} input and output vectors, respectively. The relation between the inputs and outputs of the NN is defined as

$$\mathbf{o}_p = \mathbf{x}_p^{\text{out}} = f_{NN}(\mathbf{w}, \mathbf{x}_p). \tag{4}$$

Moreover, let $x_{i,p}^s (1 \le s \le out)$ be the output of the i^{th} neuron in the s layer for the p^{th} sample, and w_{ij}^s be the weight from the j^{th} neuron of the $s-1$ layer to the i^{th} neuron of the s layer, the input-output relationship of the neuron is given by (5) and (6). Note that $s = out$ denotes the output layer.

$$x_{i,p}^s = f(z_{i,p}^s), \tag{5}$$

$$z_{i,p}^s = \sum_j w_{ij}^s \cdot x_{j,p}^{s-1}, \tag{6}$$

where $f(z_{i,p}^s)$ and w_{ij}^s denote the activation function and a component of the weight vector $\mathbf{w}$, respectively. The update formula of SGD is defined as (7) using learning rate η.

$$w_{ij}^s(t+1) = w_{ij}^s(t) - \eta \frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s}. \tag{7}$$

where t denotes the iteration number and

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s} = \frac{1}{b} \sum_{p \in X} \frac{\partial E_p(\mathbf{w})}{\partial w_{ij}^s}, \tag{8}$$

is the stochastic gradient, which is expansion by chain rule as (9).

$$\begin{aligned} \frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s} &= \frac{1}{b} \sum_{p \in X} \frac{\partial E_p(\mathbf{w})}{\partial x_{i,p}^s} \cdot \frac{\partial x_{i,p}^s}{\partial z_{i,p}^s} \cdot \frac{\partial z_{i,p}^s}{\partial w_{ij}^s} \\ &= \frac{1}{b} \sum_{p \in X} \frac{\partial E_p(\mathbf{w})}{\partial x_{i,p}^s} \cdot f'(z_{i,p}^s) \cdot x_{j,p}^{s-1}, \end{aligned} \tag{9}$$

where $f'(z_{i,p}^s)$ is the derivative of the activation function and the partial differentiation of $\partial E_b(\mathbf{w})/\partial w_{ij}^s$ varies depending on whether the s is the output ($s = out$) or the hidden layers.

- *s is the output layer ($s = out$)*:

If s is the output layer, the partial differentiation of $\partial E_b(\mathbf{w})/\partial w_{ij}^s$ is directly derived from the error function. Here, the two types of error functions, that is, the mean squared error (MSE) and the cross entropy (CE) are considered.

<MSE >

The error function is defined as

$$E_b(\mathbf{w}) = \frac{1}{b} \sum_{p \in X} \sum_{i=1}^{L} \frac{1}{2} \left(d_{i,p} - x_{i,p}^{out} \right)^2, \tag{10}$$

where L is the number of the output units and $d_{i,p}$ denote i^{th} unit of the output layer for the p^{th} desired vector. Therefore, the partial differentiation of $\partial E_b(\mathbf{w})/\partial w_{ij}^s$ is given by

$$\begin{aligned} \frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s} &= \frac{1}{b} \sum_{p \in X} \frac{\partial E_p(\mathbf{w})}{\partial x_{i,p}^s} \cdot f'(z_{i,p}^s) \cdot x_{j,p}^{s-1} \\ &= -\frac{1}{b} \sum_{p \in X} (d_{i,p} - x_{i,p}^{out}) \cdot f'(z_{i,p}^s) \cdot x_{j,p}^{s-1}. \end{aligned} \tag{11}$$

<CE >

The error function and the activation function are defined as (12) and the softmax function of (13), respectively.

$$E_b(\mathbf{w}) = -\frac{1}{b}\sum_{p\in X}\sum_{i=1}^{L} d_{i,p}\log(x_{i,p}^{out}), \tag{12}$$

$$x_{i,p}^{out} = f(z_{i,p}^{s}) = \frac{exp^{(z_{i,p}^{s})}}{\sum_{i=1}^{L} exp(z_{i,p}^{s})}. \tag{13}$$

where L is the classification class. The gradient is given by

$$\begin{aligned}\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^{s}} &= \frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial x_{i,p}^{s}}\cdot f'(z_{i,p}^{s})\cdot x_{j,p}^{s-1}\\ &= -\frac{1}{b}\sum_{p\in X}(d_{i,p}-x_{i,p}^{out})\cdot x_{j,p}^{s-1}.\end{aligned} \tag{14}$$

- *s is a hidden layer*:

If s is the hidden layer, the partial differentiation of $\partial E_p(\mathbf{w})/\partial x_{i,p}^{s}$ in (9) is given by

$$\frac{\partial E_p(\mathbf{w})}{\partial x_{i,p}^{s}} = \sum_{k}\frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot\frac{\partial x_{k,p}^{s+1}}{\partial z_{k,p}^{s+1}}\cdot\frac{\partial z_{k,p}^{s+1}}{\partial x_{i,p}^{s}} \tag{15}$$

$$= \sum_{k}\frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot f'(z_{k,p}^{s+1})\cdot w_{ki}^{s+1}. \tag{16}$$

Substituting (16) into (9), the gradient of $\partial E_b(\mathbf{w})/\partial w_{ij}^{s}$ can be obtained as (17).

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^{s}} = \frac{1}{b}\sum_{p\in X}\sum_{k}\frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot f'(z_{k,p}^{s+1})\cdot w_{ki}^{s+1}\cdot f'(z_{i,p}^{s})\cdot x_{j,p}^{s-1}. \tag{17}$$

(17) shows that the inner product of the back propagation components $\partial E_p(\mathbf{w})/\partial x_{k,p}^{s+1}\cdot f'(z_{k,p}^{s+1})$ and the weights w_{ki}^{s+1} is necessary for the all samples in a mini-batch b. This means that the derivation of the gradient requires b times backward processes. The structural diagram of SGD is shown in Fig. 1. This figure also shows that SGD requires an error propagation architecture from the output layer to the input layer for each training sample in order to calculate the gradient.

III. Stochastic Weight Difference Propagation Learning

In this paper, to reduce the computational cost of training in SGD, Stochastic Weight Difference Propagation (SWDP) is proposed. The proposed SWDP focuses on the backpropagation stream of each training sample in SGD training and eliminates the BP architecture requirement for each training sample in a mini-batch. As a result, SWDP can calculate the amounts of weight updates with only one weight difference propagation. This means that the proposed method can reduce the computational complexity in the backward calculations of the training to $1/b$ compared to SGD.

Since the training of SWDP is based on SGD, and the computation process differs depending on whether s is the output or hidden layers.

- *s is the output layer (s = out)*:

If s is the output layer, $\partial E_b(\mathbf{w})/\partial w_{ij}^{s}$ is same as SGD given by (11) or (14).

- *s is the hidden layer*:

If s is the hidden layer, a variant of (17) is considered. In the proposed SWDP, the gradient of $\partial E_b(\mathbf{w})/\partial w_{ij}^{s}$ given by (17) is transformed as follows:

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^{s}} = \frac{1}{b}\sum_{p\in X}\sum_{k}\frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot f'(z_{k,p}^{s+1})\cdot w_{ki}^{s+1}\cdot f'(z_{i,p}^{s})\cdot x_{j,p}^{s-1} \tag{17}$$

$$= \sum_{k} w_{ki}^{s+1}\cdot\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot f'(z_{k,p}^{s+1})\cdot f'(z_{i,p}^{s})\cdot x_{j,p}^{s-1}. \tag{18}$$

Here, (18) is transformed to (19) by assuming that the output of i^{th} neuron in s layer $x_{i,p}^{s}\neq 0$.

$$\begin{aligned}\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^{s}} = \sum_{k} w_{ki}^{s+1}\cdot\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot f'(z_{k,p}^{s+1})\cdot x_{i,p}^{s}\\ \cdot\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}.\end{aligned} \tag{19}$$

From (9),

$$\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}} = \frac{\partial E_p(\mathbf{w})}{\partial x_{k,p}^{s+1}}\cdot f'(z_{k,p}^{s+1})\cdot x_{i,p}^{s}. \tag{20}$$

Therefore, (21) can obtained by substituting (20) into (19).

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^{s}} = \sum_{k} w_{ki}^{s+1}\cdot\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}\cdot\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}. \tag{21}$$

Here, (21) is transformed as follows: The second sum in (21) for the sample p is divided into two parts, that is, $\partial E_p(\mathbf{w})/\partial w_{ij}^{s}$ and $f'(z_{i,p}^{s})/x_{i,p}^{s}\cdot x_{j,p}^{s-1}$. Then (21) is rewritten as (22),

$$\begin{aligned}\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^{s}} = \sum_{k} w_{ki}^{s+1}\Bigg\{&\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}\cdot\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}\\ &+\frac{1}{b}\sum_{p\in X}\left(\left(\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}-\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}\right)\right.\\ &\left.\cdot\left(\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}-\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}\right)\right)\Bigg\}.\end{aligned} \tag{22}$$

That is, the first term denotes the product of the averages of $\partial E_p(\mathbf{w})/\partial w_{ki}^{s+1}$ and $f'(z_{i,p}^{s})/x_{i,p}^{s}\cdot x_{j,p}^{s-1}$. The second term is the covariance of these parts. In (22), if $\partial E_p(\mathbf{w})/\partial w_{ki}^{s+1}$ and $f'(z_{i,p}^{s})/x_{i,p}^{s}\cdot x_{j,p}^{s-1}$ are independent variables, (23) holds.

$$\begin{aligned}&\left(\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}-\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}\right)\\ &\cdot\left(\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}-\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^{s})}{x_{i,p}^{s}}\cdot x_{j,p}^{s-1}\right)=0\end{aligned} \tag{23}$$

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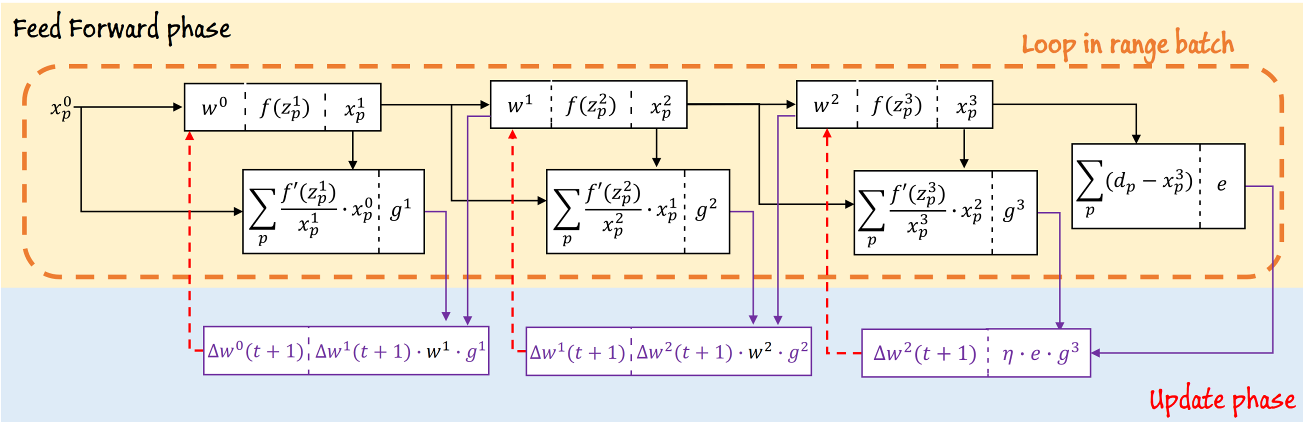

Fig. 2. Structural diagram of SWDP.

However, these terms are clearly not independent because these parts are derived from the sample p. It is also estimated that as the number of samples in the mini-batch increases, the value of (23) becomes larger. On the other hand, it is clear that learning of NN can be performed even if there is some error in gradients [3]–[6]. Therefore, the proposed SWDP assumes that (23) holds and then obtains (24).

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s} \simeq \sum_k w_{ki}^{s+1}\left(\frac{1}{b}\sum_{p\in X}\frac{\partial E_p(\mathbf{w})}{\partial w_{ki}^{s+1}}\cdot\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^s)}{x_{i,p}^s}\cdot x_{j,p}^{s-1}\right)$$
$$=\sum_k\left(\frac{\partial E_b(\mathbf{w})}{\partial w_{ki}^{s+1}}\cdot w_{ki}^{s+1}\right)\cdot\left(\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^s)}{x_{i,p}^s}\cdot x_{j,p}^{s-1}\right). \tag{24}$$

In this study, the gradient $\partial E_b(\mathbf{w})/\partial w_{ij}^s$ of (24) is used for learning. Consider the update formula for w_{ki}^{s+1} in SGD of (25).

$$w_{ki}^s(t+1) = w_{ki}^s(t) - \eta\frac{\partial E_b(\mathbf{w})}{\partial w_{ki}^s}. \tag{25}$$

Here, the update formula of (25) can be transformed into an expression for the amount of update (difference) Δw_{ki}^{s+1} as

$$\Delta w_{ki}^{s+1} = w_{ki}^{s+1}(t+1) - w_{ki}^{s+1}(t) = -\eta\frac{\partial E_b(\mathbf{w})}{\partial w_{ki}^{s+1}}, \tag{26}$$

and then

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ki}^{s+1}} = -\frac{1}{\eta}\Delta w_{ki}^{s+1}. \tag{27}$$

By substituting (27) into (24),

$$\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s} = \sum_k\left(-\frac{1}{\eta}\Delta w_{ki}^{s+1}\cdot w_{ki}^{s+1}\right)\cdot\left(\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^s)}{x_{i,p}^s}\cdot x_{j,p}^{s-1}\right). \tag{28}$$

Furthermore, by substituting (28) into the SGD update formula (7), the proposed SWDP update formula can be obtained as (29).

$$w_{ij}^s(t+1) = w_{ij}^s(t) - \eta\frac{\partial E_b(\mathbf{w})}{\partial w_{ij}^s}$$
$$= w_{ij}^s(t) + \sum_k\left(\Delta w_{ki}^{s+1}\cdot w_{ki}^{s+1}\right)\cdot\left(\frac{1}{b}\sum_{p\in X}\frac{f'(z_{i,p}^s)}{x_{i,p}^s}\cdot x_{j,p}^{s-1}\right). \tag{29}$$

In (29), $\left(1/b\sum_p f'(z_{i,p}^s)/x_{i,p}^s\cdot x_{j,p}^{s-1}\right)$ can be calculated in the forward operation in the mini-batch. Therefore, the backward operation for the learning of NN is one calculation of $\sum_k\left(\Delta w_{ki}^{s+1}\cdot w_{ki}^{s+1}\right)$ in the stochastic learning. This means that the learning architecture is simple, and the computational cost decreases compared to SGD. However, it is estimated that the error of the gradients affects the learning from the assumption of (23) holds. In Section V, the effect on learning is investigated through computer experiments. The structural diagram of SWDP is shown in Fig. 2. This figure shows that SWDP eliminates the requirement of the BP architecture for each training sample in mini-batch and calculates the amounts of the weight update with only one weight difference propagation.

IV. Computational Cost

This section discusses the computational costs of the proposed SWDP and SGD for updating a weight of w_{ij}^s. Since the forward calculations of SWDP and SGD are the same, the calculation costs of the backward processes for both SWDP and SGD are compared. The summary of the backward computational cost is illustrated in TABLE I. To estimate the costs of backward processes, (17) and (28) are considered for SGD and SWDP, respectively. In SGD, the computational cost is $b(2k+2)$, which denotes the inner product of the propagated error components and weights in the $s+1$ layer for all samples in the mini-batch b. In SWDP, the cost k indicates the inner product of weights and their differences in the $s+1$ layer. Therefore, it can be seen from TABLE

I that the proposed SWDP can reduce the computational complexity in the backward calculations of the training to $1/b$ compared to SGD. Here, the computational cost of $\left(1/b \sum_{p \in X} f'(z^s_{i,p})/x^s_{i,p} \cdot x^{s-1}_{j,p}\right)$ in (28) is $2b+1$, but this term can be calculated in forward process. Therefore, this cost is ignored in the backward process of SWDP.

TABLE I
SUMMARY OF THE COMPUTATIONAL COST.

Algorithm	Computational Cost of Backward
SGD	b(2k + 2) + 1
SWDP	k + 1

V. Simulation Results

To investigate the performance of the proposed method, SWDP is compared with SGD on two classification benchmark problems. For all problems, the learning rate is set to $\eta = 0.1$ for both algorithms. The mini-batch sizes are set to $b = 1, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20,$ and 32 for the problems. The termination condition were set to $E(\mathbf{w}) < 10^{-3}$ and the maximum iteration counts $t_{max} = 500,000$.

A. 8×8 MNIST

The first problem is the classification problem of MNIST handwritten digits dataset [10] with 8×8 pixels as shown in Fig. 3. The 8×8 MNIST problem classifies a handwritten digit image of $|T| = 1,797$ training data samples into ten classes from 0 to 9. In this experiment, the dataset was randomly divided to 75% (1,347) as the training data T_r and 25% (450) as the test data T_s. The network structure is 64-10-10, which denotes inputs, the number of neurons in a hidden layer, and the outputs. In this problem, the activation functions for the hidden and the output layers were set to the sigmoid and the softmax of (13) functions, respectively. The error function is cross-entropy of (12). The experimental results are shown in Fig. 4 and TABLE II. In the first, Fig. 4 shows the training and test accuracies for each mini-batch size, where the x-axis is the mini-batch size, and the y-axis is the accuracy. This figure shows that the training accuracies of SGD and SWDP are almost the same. In terms of test accuracy, both algorithms maintain almost the same accuracy too. That is, SWDP was up to 3% less accurate than SGD. Therefore, it concluded that training with almost the same accuracy is possible even if simplified backward calculation. The table summarizes the epoch, iteration, time, and time per iteration required for the convergence of SGD and SWDP. The table shows that SWDP requires more epoch, iteration, and time as the mini-batch size increases. It can be attributed to (23) becoming stronger as the mini-batch size increases. However, the computation time per iteration of the proposed SWDP is shorter than SGD because the backward computation is simplified. Therefore, it can be concluded that the proposed SWDP method is practical for this problem.

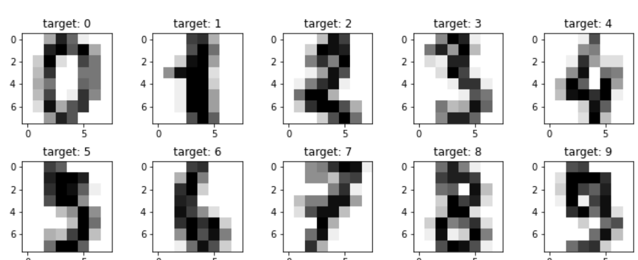

Fig. 3. Examples of 8×8 MNIST handwritten digits dataset.

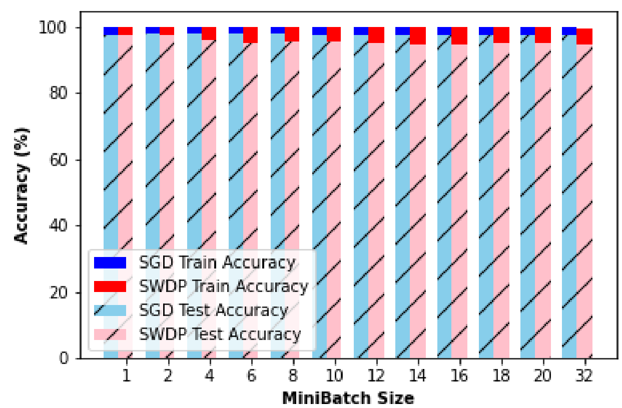

Fig. 4. Accuracy .vs. mini-batches for 8×8 MNIST.

B. 3-Spiral

The next problem is another nonlinear problem called the 3-Spiral problem [11]. 3-Spiral is a problem of classifying training data samples $T_r = 1,050$ into three classes, as shown in Fig. 5, where each class has 350 data samples. The input data is the coordinates of each point, and the NN structure is 2-10-3, which denotes inputs, hidden layer neurons, and outputs numbers, respectively. The activation and error functions were the same as the previous problem. The experimental results are shown in Fig. 6. Fig. 6 shows the training accuracy for each mini-batch size, where the x-axis is the mini-batch size, and the y-axis is the training accuracy. This figure shows that the proposed method and SGD have similar accuracy when the mini-batch size $b = 1$ and 2. However, as the mini-batch size increases, the accuracy of the proposed SWDP method decreases from 3% to a maximum of 22% ($b = 10$). Therefore, in training this problem, the training of SWDP strongly depends on the mini-batch size and the initial values.

VI. Conclusion

In this research, a novel training algorithm was proposed. The proposed method was referred to as Stochastic Weight Difference Propagation (SWDP) to simplify the gradient calculation (backward processes) in SGD. SGD, based on the error propagation architecture from the output to the input layers, is required for each training sample to calculate the gradient and

TABLE II
THE RESULTS SUMMARY OF 8×8 MNIST.

Algorithm	Mini-batch Size	Epoch	Iteration	Time (*sec*)	per Iteration Time(*msec*)
SGD	1	28	39,062	0.364	0.9318×10^{-2}
	2	26	18,170	0.32	0.1761×10^{-1}
	4	26	9,071	0.284	0.3130×10^{-1}
	6	26	6,047	0.284	0.4696×10^{-1}
	8	26	4,535	0.268	0.5909×10^{-1}
	10	27	3,751	0.276	0.7358×10^{-1}
	12	26	3,023	0.262	0.8666×10^{-1}
	14	26	2,591	0.277	0.1069
	16	26	2,267	0.268	0.1182
	18	26	1,997	0.27	0.1352
	20	26	1,808	0.263	0.1454
	32	27	1,175	0.274	0.2331
SWDP	1	28	39,062	0.366	0.9369×10^{-2}
	2	92	62,588	0.947	0.1513×10^{-1}
	4	192	64,847	1.826	0.2815×10^{-1}
	6	625	140,223	5.614	0.4003×10^{-1}
	8	860	144,647	7.691	0.5317×10^{-1}
	10	1,233	165,355	10.943	0.6617×10^{-1}
	12	2,254	252,559	19.474	0.7710×10^{-1}
	14	3,312	318,047	28.558	0.8979×10^{-1}
	16	4,922	413,499	41.972	0.1015
	18	5,006	370,517	42.398	0.1144
	20	5,898	395,232	50.48	0.1277
	32	11,905	500,000	99.671	0.1993

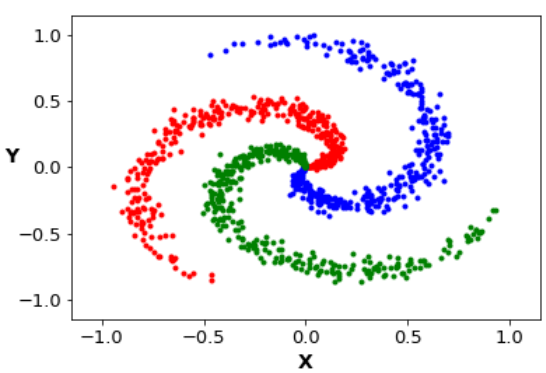

Fig. 5. Layout of the 3-Spirals dataset.

causes an increase in hardware and computational costs. The proposed SWDP was focused on the disadvantage of SGD and reduced the computational complexity in the backward calculations of the training compared to SGD. The proposed SWDP simplifies the backward process of SGD using only the inner product of the weights and their differences in training. The computational costs of the backward processes during SWDP training are reduced to $1/b$ (b is the mini-batch size) compared to SGD. Experimental results showed that SWDP could learn accurately close to SGD even when the backward processes were simplified. However, the number of epochs

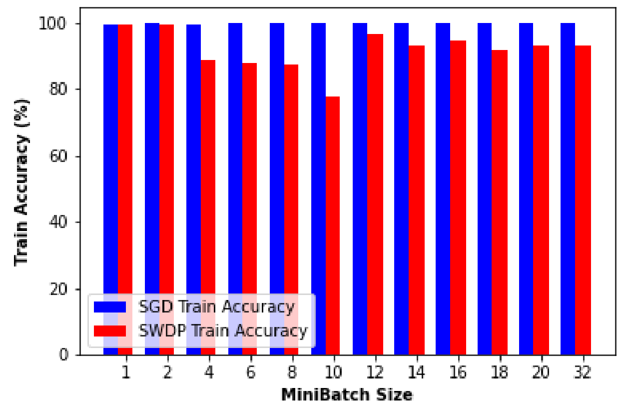

Fig. 6. Training accuracy for mini-batches for 3-Spirals.

required for learning SWDP increased as the mini-batch size increased. This is caused by the fact that SWDP ignored the covariance term required for the SGD backward processes.

In future works, the proposed method SWDP will be improved to achieve more robust learning similar to SGD regardless of the mini-batch size, initial values, and nonlinearity of the problem. In addition to investigating the effectiveness of the proposed method on edge computing, we plan to implement SWDP on hardware such as FPGA to verify its effectiveness.

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