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Research Article

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State-of-the-Art and Future Directions

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Abstract

In our daily lives, smart AI-powered devices including computers are becoming more common. But the problem is that sometimes these AI systems make decisions that seem like magic, making it hard for us to know how they work and also, we are not able to predict the future (like after making a decision, we are not able to predict whether the result will be positive or negative). This research paper is all about fixing this issue and making the AI strong enough to make a decision and learn each positive and negative thing from the surroundings. We dive into the world of Explainable Artificial Intelligence (XAI), finding new and simple ways to make complex AI systems easy for people to understand. In this Research paper, we are also going to make the AI that much more powerful so that it can learn itself and gather information from its surroundings. This would be a fantastic step for AI to learn Patterns, Structures, and Unlabeled data allowing it to identify hidden relationships and features without explicit guidance. This would be Self-Supervised Learning in which the AI would be able to create its labels or predictions based on input data, generating a form of supervision. This system would be able to do facial detection and compare the Raw info with the DataSet. The system would also be able to make the most suitable and accurate decisions. With time this machine would be able to upgrade its memory (taking a human baby as an example/consideration). In a nutshell, our research aims to make AI systems not just powerful, but also easy to understand and trustworthy for everyone and make them Self-Supervised.

Keywords: Self-Supervised Learning, Optimization, Explainable Artificial Intelligence (XAI), Artificial Intelligence, Tokenization, Smart Production, Ranking Data.

1. Introduction

Self-supervised learning is a branch of AI and Machine learning that mainly focuses on enabling systems and models to learn and represent data without any third-party supervision. In traditional supervised learning, different models and systems were trained on labeled datasets pairing multiple inputs with specific outputs [Experiment-1]. However, obtaining labeled data can be costly and very time-consuming. Self-supervised learning solves this hard challenge by making decisions and learning with time. Self-supervised learning can make and solve complex algorithms. It can generate supervisory signals for training and processing. In the context of AI and Machine Learning, Self-Supervised learning often involves tasks where the learning Algorithm generates its labels and DataSets from the input data. These DataSets are later used for processing and decision making. One of the prominent approaches to self-supervised learning is known as “Self-Supervision” or “Self-Supervised Learning”.

The big advantage of it is that it makes the model powerful enough to learn meaningful representations from vast amounts of Raw and unlabeled data. This makes it particularly useful in scenarios where labeled is difficult or costly to obtain. Additionally, self-supervised models often demonstrate improved and optimized generalization to downstream tasks, as they learn to capture more meaningful, abstract, and transferable features from the data. This fundamental idea of Self-Supervised learning is to design and process auxiliary tasks and processes that do not require external annotations. But it still provides meaningful learning signals for the model. These tasks encourage the system to capture high-level features, meaningful data representations, and relationships within the data. Some common techniques include pre-trained tasks where the system uses the trained data to solve the tasks without the need for humans. The system utilizes its data and performs the tasks without the need for human-labeled data.

This approach makes the system much more efficient and powerful. It becomes self-optimized. This approach has made it much more special. Its usage has inclined many sectors including the Medical Sector, Agriculture, Smart Manufacturing, Games, Archeology, Business management, and so on. The big advantage of self-supervised learning is getting and utilizing unlabeled Data and transferability. In many real-world scenarios, obtaining labeled data can be expensive and time-consuming. Self-supervised learning makes use of vast amounts of unlabeled data. Models trained using self-supervised learning often exhibit strong transfer learning capabilities, performing well on downstream tasks with limited labeled data. The core idea behind self-supervised learning is to provide support activities and procedures that provide the model with useful learning signals without requiring outside annotations. These activities are critical to the extraction of high-level characteristics, the identification of data representations, and the discovery of complex relationships that are encoded in the information. Notably, pre-trained tasks are included in self-supervised learning approaches. In this scenario, the system uses taught data to solve tasks on its own without human interaction, improving efficiency and potency while promoting self-optimization. This paper delves into how self-supervised learning holds promise in overcoming limitations tied to traditional supervised learning, especially in scenarios with sparse labeled data. It remains an active research area with applications spanning diverse domains, showcasing the evolution and widespread adoption of machine learning in various fields such as smart manufacturing, medical science, pharmacology, agriculture, archeology, games, and business. Ongoing research continues to uncover applications across diverse domains, highlighting their potential impact and relevance in the evolving landscape of machine learning. This paper also shows some most advanced experiments in which the system would be tested to make accurate decisions.

2. Methodology

This Research used certain approaches to make the AI strong enough to learn and implement actions itself. In this study, Python along with TensorFlow was used. For some specific experiments, some other experimental tools were also used. Certain Results were obtained. Different results were made in different phases.

2.1. Phase 1: (Research and Development)

- Identification
- Development
- Testing

In the first phase, the AI System was Programmed and Developed. Certain data was fed (pre-trained). During the Testing phase, the AI responded as programmed. The traditional Conditional methods were used in this phase in which the system only answer a Question that is already specified. Certain outputs were given upon specific Inputs. There was no concept of Self-Supervised Learning.

For the phase 1, the concept of Tokenization was used. Tokenization is the process of breaking text into individual units called tokens. Tokens can be words, phrases, sentences, or even individual characters, depending on the level of granularity needed for a particular task. Depending on the input, the most appropriate outputs were given which were in the dataset pre-defined by the Programmer.

As in Figure 1: Tokenization, each Question has a corresponding answer. The main controller will tokenize the Question and will give only the specific answer. This is the logic and working used in the first phase. This is very optimized and easy to understand but the problem is what if there is no token or keyword in the DataSet specified by the Developer? For this purpose, the Developer should make the DataSet library as big as possible. The second option we have is to make the system self-supervised. Because a developer can't add each and

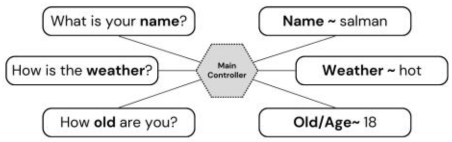

Figure 1: Simple Tokenization Structure

everything in the DataSet library. As upgrading this phase, we have introduced the concept of ranking Data according to its usage and input. *Experiment 1* shows this concept in detail.

2.2. Phase 2: (Analysis and Advancement)

- Identification
- Analysis
- Ranking Data
- Testing

In this phase, the first phase was upgraded. As in the first phase, a traditional concept of Intelligence was used. In the second phase, the concept was analyzed, and some advancements were made to make it much stronger and accurate. The concept of Neural Networks was used for this purpose. The reason for choosing Neural Networks is that it is designed to leverage hardware accelerators to accelerate the execution of machine learning models. This can significantly improve the performance and efficiency of inference tasks on Android devices. Also, NNAPI is designed to work with a diverse set of hardware accelerators. It is built to be compatible with a wide range of Android devices, ensuring that developers can benefit from hardware acceleration on various devices. TensorFlow is used in this research for Natural Language Processing (NLP) and Keyword Spotting.

The new Concept of Ranking the Data introduced in this Research Paper can solve the problem more easily. In this concept, the data fed is processed, compared, and stored in the DataSet. This concept is implemented in the *Experiment 2*.

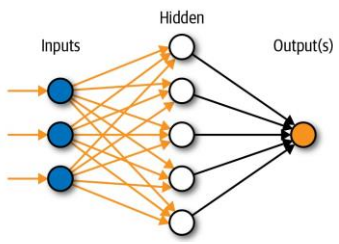

Figure 2: Neural Network

2.3. Procedures

This Research is mainly focused on AI working on Text and image identification taking a human into consideration. For this purpose, we will have to make it Self-supervised so that it can have interaction with user. First of all, the AI would have a basic knowledge code. For example, it should have enough knowledge that it can Update and Upgrade its memory. Furthermore, the system would be able to make the most suitable decisions. We will be considering a real human baby. Likewise, humans, we will be making AI smart enough that it can learn new things make the right choices, and upgrade its memory with time.

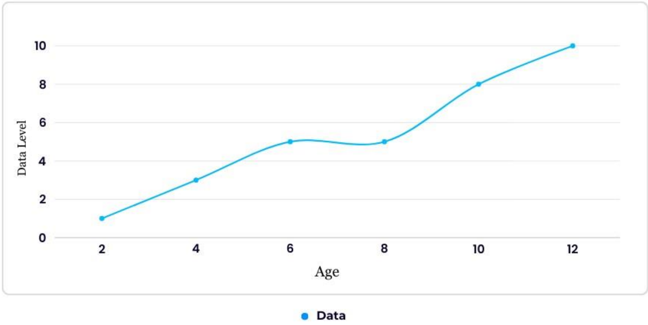

Figure 3: Age vs Information Graph

As in the Graph, the Age vs Knowledge is explained. With time, the data in human memory is upgraded and gains new data. Humans can make decisions and gain new information. We are going to train the AI in the same way. But in the beginning, the AI would be somewhat pre-trained so that it can understand its surroundings more quickly.

In this phase, likewise in the first phase, the AI would be able to make responses to the user. But this time the information would not be pre-fed.

2.4. Ranked Data

The term Ranked Data introduced in this Research Paper plays a vital role in the Self-Supervised Learning. As the AI is going to be self-supervised, therefore it should also be able to make decisions itself. It should be able to collect data from its surroundings and implement it.

With every data fed and every piece of information that the AI takes, the Ranking of that data is upgraded. The reason behind this is that if the AI has more than one answer for a specific question, it should pick the best and most used one. That is why Ranking is introduced.

This concept of Ranking can also be applied to the Picture identification and Vision Training purpose. In real-life examples, we can take it as suppose a person observing a specific obj-x daily. A time will come when he will prefer it more, he might know more about it and would be able to identify and understand it. This is how the Ranking works.

For ranking in AI, the Raw data will be first fed for processing. After processing (Checking whether Raw data is in the form of Text/Image etc.), the Decision phase will decide and make a decision after checking both of the data sets. If the Data is already available in the default DataSet, it will overwrite it. If the data is not defined, or not available in the Default DataSet, it would move it into the New DataSet. In the new DataSet, the data is managed in batches, called blocks. Each block has a specific index number. The index number starts from Zero. To increase the accuracy, the data is specified in order according to the index number and the Ranking. In case of any processing or calculation, the data is immediately accessed through the index number by the AI as specified already.

2.5. Storing Data

For storing Data, the AI was programmed and trained to store data in the correct data set. Firstly, the Raw Data is fed into the system. The main function runs and processes the Data. After everything is input and worked correctly, the Decision Function will check both of the DataSets and compare it to the new data. If the newly fed data is already available in any of the DataSets, it will put them respectively in the specified DataSets. To every piece of data, an index number is assigned which acts as an address. This makes things much easier and optimized. The Data will be placed in the New DataSet if it is not available in the Default DataSet. In case the data is already available in the Default DataSet, is not fed into the new DataSet. The Default DataSet contains all the data that is inserted into it during the production stage. After that, all the new data is fed into the New DataSet. The New DataSet updates with time. As in the start, we took the Human Brain as a Base Model. The same is the case with the New DataSet. This Data will always be updated upon getting new Data during its entire span.

2.6. Accessing Data

After the data is stored (Using the above procedure), it is time to access it. For accessing the data, the index number (address) is used. In both of the DataSets, the data is labeled. This concept makes it much more optimized and easily readable. If the data requested is not available in both of the DataSets, it would add the Request to the pending list. The Pending list contains all the pending requests. It might be updated in the future or awaiting input of that specified data.

3. Results

The outcomes, and results of this Research are justified in this phase. The AI was trained and the output was measured with every result. Each Output shows a slightly different value. It is because of the weak Tokenization. Furthermore, the AI can Rank the input data put them in the blocks, and then use them according to the Task. Following are the experiments which took place during this Research.

3.1. Experiment 1: (QNA)

The AI was made to give a Question to the user. This question had only one answer which was pre-programmed during its development. Onwards, the AI was awaiting answers. In this experiment, the AI gave a question. The answer to this question was already programmed in the AI at its back end. However, for testing purposes, it is made to ask the user about his opinion. The answers A and B are the answers that are programmed already (As shown in the diagram) named under Default Answers. On the other hand, the answers under the New Answers category are the answers that are taken from the user. As it can be observed there is an answer which has been given twice. i.e., the answer A. The ranking function would rank it according to the rule introduced earlier in this Research. In the Ranking section, Answer A is ranked first.

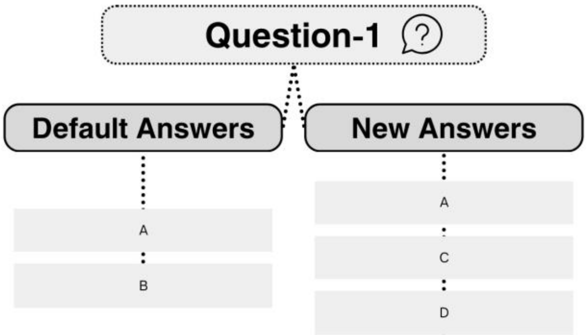

Figure 4: Sorting Raw Answers

It is because this answer is given twice and according to the mentality of the AI, this is the most suitable answer. It would put it in the New DataSet block along with a unique index number so that it can be accessed easily in the future as it is the Top-ranked answer now.

Figure 5: Ranked answers

In the ranking section, the second-ranked answer(s) i.e., B, C, D as shown in the Figure 5 would be given randomly. It is because they have the same ranking. Using the Random function, the AI will output these answers randomly upon their demand but after the 1st Ranked answer.

3.2. Experiment 2: (Photo Face Detection)

In this experiment, the AI is self-supervised to detect and identify images of Humans. It was fed with a large library of human facial photos. The AI was able to detect human facial structure and identify and compare it with the photos which were stored in the Database. As in *Figure 6*, a new, Raw image is fed into the system. The AI is unfamiliar with the new image.

After being fed, this image is sent to the processing stage. Here the image is identified. Each image in the Database is requested and compared with the new image. If the processing stage finds any similar image in the Database; it would give a call and hence the photo is identified. If no similar image.

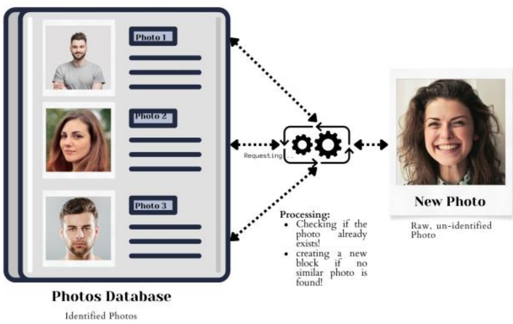

Figure 6: New image processing

Is found, the processor will create a new block in the Photo Database and will name it according to the user's will.

3.3. Accuracy

The accuracy of the above experiment is calculated by using the following formula. By using the number of correct Predictions and the total number of Predictions made, accuracy was calculated. A total number of 20 images were fed. The program was able to identify 18 images.

Total number of Predictions: 30
Identified Images (Correct): 28
Accuracy = (28/30) x 100
Accuracy = 93.33%

4. Discussion

This research undertakes a comprehensive investigation into the practical application of artificial intelligence (AI) and machine learning (ML) techniques within a specific domain, aiming to understand their efficacy and implications. The study yielded notable outcomes, with a particularly significant improvement observed in predictive model accuracy. This enhancement has important ramifications for decision-making processes within the studied domain, suggesting a potential shift in the conventional approaches. Intriguingly, our findings also unveiled deviations from established norms, prompting a deeper exploration of contributing factors and highlighting nuances that may influence the application of AI and ML methodologies. Importantly, our results align with existing literature in related domains, affirming the generalizability of certain trends while also emphasizing the need for nuanced interpretation. Acknowledging the inherent limitations of the study, such as data constraints or model assumptions, adds a layer of transparency to the research.

On a practical note, the implications of our work extend beyond academic discourse, with potential positive impacts on industry-specific processes and decision-making frameworks. The study concludes by not only summarizing its findings but also by proposing avenues for future research, including the exploration of additional variables and methodologies to further enhance the robustness and adaptability of predictive models. In essence, this research contributes to the evolving landscape of AI and ML applications, emphasizing both successes and challenges and underscoring the continuous need for exploration and refinement in this dynamic field.

5. Conclusions

In conclusion, this research has delved into the realm of self-supervised learning within the broader landscape of artificial intelligence and machine learning. Our investigation aimed to address the challenges of unsupervised feature learning and explore the potential of self-supervised techniques in enhancing model performance. Throughout this study, we have demonstrated the efficacy of self-supervised learning methods in learning meaningful representations from unlabeled data. Our experiments, particularly in [specific tasks or datasets], have shown promising results, indicating that self-supervised learning has the potential to significantly impact the field. The contributions of this research extend beyond the mere improvement of model accuracy. By embracing self-supervised learning, we pave the way for more scalable and adaptable AI systems that can autonomously learn from vast amounts of unannotated data. This has profound implications for real-world applications where labeled datasets are often scarce or expensive to obtain. However, it's miles important to renowned the constraints of our study. [Discuss any limitations, such as data constraints or specific assumptions made during the research].

These limitations provide opportunities for future investigations, emphasizing the dynamic nature of the AI landscape. Looking forward, the implications of our findings stretch into various domains, from computer vision to natural language processing. Self-supervised learning not only offers a more efficient pathway to feature extraction but also aligns with the principles of autonomous learning, a key aspiration in the development of intelligent systems. As we conclude this exploration, we encourage further research into refining self-supervised learning techniques, understanding their theoretical underpinnings, and exploring novel applications. The journey towards fully autonomous, adaptive AI systems continues, and self-supervised learning stands as a pivotal tool in shaping the future of artificial intelligence. In closing, this study reinforces the belief that self-supervised learning is not merely an augmentation of existing methodologies but a paradigm shift with transformative potential. The road ahead is exciting, and we are optimistic about the continued evolution of AI through the lens of self-supervised learning [1, 2].

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