International Conference on Science, Engineering & Management Trends

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Digital Forgetting: Is Selective Memory Essential for Artificial Intelligence?

Anisha Singh, Anubha Khanna, Ansh Goyal, Abhijeet Sharma
Chitkara University Institute of Engineering & Technology Punjab , India

Abstract- - Selective forgetting is a natural part of the human thinking that enables the effective thought preparation, plasticity and decision making. By doing so, humans are unable to store the information indefinitely but this way they prioritize the knowledge that is related and eliminates irrelevant and outdated information with the course of time. The outcome of this process is that this avoids overloading of memory, allows adaptive thinking as well as flexible generalization functions, which are not easily replicated by the existing artificial intelligence (AI) systems. In comparison, the existing AI systems are primarily designed with the paradigm in which continuous data storage is useful in that the more a data is stored, the more effective the performance is developed. However, this approach has drawbacks such as being slowed by computer, overfitting, reinforcing bias, maintaining stale knowledge, and privacy. Being a concept of machine learning, forgetting may be used as pruning to improve generalization; it may be used as a concept in cognitive science, it may help to eliminate irrelevant or damaging information; and as an ethical concept, it can be used with the issue of the right to be forgotten in legislation, such as the GDPR. The article inspecks the notion of whether intentional/ algorithmic forgetting is necessary to develop Artificial General Intelligence (AGI). Theoretical memory management model is also adopted through imports of the significance, frequency of use and time based wear to evaluate and optimize data relevance. This model is utilized with the assistance of a system called ForgetAI that demonstrates the optimization of memory in real-time with the aid of scoring and filtering systems. Through experimentation, it has demonstrated that selective forgetting relieves memory load without any noticeable effect on system performance and plasticity. This paper thesis is that the concept of an ideal memory retention may not be most intelligent system-wise and that controlled forgetting can enhance efficiency, equality and scalability. The research questions which the studies address are the following: does forgetting increase the adaptability of AGI and what can be done to optimize memory methods to transform AI systems to be more fair and human-like?

Keywords:- Digital forgetting, pruning of the memory, artificial intelligence, cognitive science, right to be forgotten and AGI adaptability.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

I. INTRODUCTION

Artificial Intelligence (AI) is one of the most important new technologies of the digital world. It has extensive applica-tions across a variety of industries, such as healthcare, fi-nance, transportation, e-commerce, and education. Exam-ples of such applications are the recommendation systems (e.g., Netflix, Amazon), virtual assistants (e.g., Siri, Alexa), fraud detectors and autonomous vehicles that require AI to process large amounts of data and come up with the smart decisions.

The principal driver of the AI systems is big data. They con-tinuously accumulate and analyze information on users, sensors and electronic platforms to augment their learning and performance. The systems traditionally are constructed based on the understanding that the more data, the greater the accuracy and the intelligence. This is a good way in the early stages but there are two issues with time as the data continue to accumulate. As the size of the data gatherings grows, they take up more storage capacity and computation opportunities and might slug presence in system execution and escalate operational costs. Moreover, not all the data stored comes in handy. As time passes, some of the data can become outdated or irrelevant and this can negatively im-pact the quality of predictions and decision-making proce-dure. Furthermore, there is also a severe threat of confiden-tiality and security with long-term storage of personal in-formation. Quite on the contrary, the intelligence of the hu-man being follows a more efficient path. Not everything is permanently stored in the human brain. Instead, it prefers to encode the important information, and forget that which is less vital or important. This inequality in forgetting allows to reduce cognitive load and to increase the efficiency of learning, and simplifies the process of decision-making. It is on this natural process that the scientists have proposed the concept of digital forgetting of artificial intelligence. Digital forgetting allows AI systems to compute the importance of the data stored, so the information that has been forgotten or is irrelevant or low value can be deleted as long as the in-formation remaining is meaningful and useful. Through this, AI systems will be in a position to be more efficient, flexi-ble, and scalable. The present research paper will focus on the issue of whether intentional forgetting is a crucial com-ponent of creating sophisticated AI engineering, in particu-lar, in the case of Artificial General Intelligence (AGI). It tries to show that more intelligent data removal can lead to better system performance, less bias and fairness, making AI systems closer to human-like intelligence.

II. PROBLEM STATEMENT

The uncontrolled expansion in data presents a number of challenges to the current AI.

- **Data Overload**

Machine learning systems are incessantly being fed a variety of information in various formats such as user interactions, sensor measurements and logs. This leads to a geometrical growth in the quantity of stored data and systems are difficult to regulate.

- **Computational Complexity**

The larger the size of the dataset, the more time it takes to process, train and make inferences. This minimizes efficiency and responsivity of the system.

- **Outdated Information**

Not all the things are useful data. Out-of-date data may be a noise and is not going to give precise forecasts of current trends.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

- **Privacy and Legal Issues.**

Retention of user information permanently is against privacy legislation such as GDPR, of the right to forget.

- **Resource Consumption**

Big data consumes bigger storage and processing facilities, raising the cost of operations.
These issues point towards the necessity of a clever system that will be able to sort and store only useful information.

III. RESEARCH CONTRIBUTION

The current research article will discuss the significance of artificial intelligence systems of digital forgetting. The main contributions of this study were as follows.

1. The article specifies the concept of digital forgetting and its motivation by the human memory processes.

2. It talks about the relevance of selective memory in artificial intelligence in achieving effectiveness and flexibility in systems.

3. The paper has discussed some of the techniques, which include machine unlearning, memory decay and data pruning that are employed to help in implementation of the digital forgetting.

4. It is given practical examples of how it can be applied to contexts of digital forgetting in recommendation systems, healthcare systems, autonomous vehicles and chatbots.

5. The research article reveals the existing issues and potential study in the future regarding the issue of digital forgetting.

IV. LITERATURE REVIEW

The Memory management in Artificial Intelligence has been a concept that has been studied more with the increasing importance of privacy and efficiency.

Cao and Yang (2015) came up with the concept of machine unlearning that allows the system, which relies on AI, to forget some data that is contained in the trained models. This is recommended due to privacy and control.

Bourtoule et al. (2021) proposed useful machine unlearning techniques, which reduce the erasure cost of data. They have shown in their work that selective forgetting can be implemented without the need to retrain entire models.

Ma et al. (2023) reviewed the techniques of machine unlearning through the use of neuron masking whereby the specific components of the neural networks are re-configured to unlearn specific information.

Wang et al. (2024) suggested representation forgetting, where the information at the feature level is removed, and it is more efficient.

International Conference on Science, Engineering & Management Trends

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Liu et al. investigated the data pruning technique, which is applied to reduce redundant or insignificant data in dataset to obtain a better performance.
Papernot et al. accentuated privacy-preserving AI, which underlines the importance of data protection of users.

Recent research confirms that memory management is the key aspect of the scalable AI systems development. Digital forgetting provides us with a viable solution to this problem.V. Significance of DIGITAL Forgetting..

V. IMPORTANCE OF DIGITAL FORGETTING

There are three theoretical foundations of digital forgetting.

1. Memory Strength

The importance of each data item and its use are used to give it a strength value. More critical and commonly used information is stronger and is stored.

2. Time-Based Decay

The value of memory decreases with time. This is simulated with exponential decay, so that older data becomes less and less relevant.

3. Reinforcement

Frequently accessed data is made stronger and is less susceptible to being deleted.

These principles guarantee that AI systems act in a similar way as the human memory systems.

VI. DIGITAL FORGETTING ARCHITECTURE

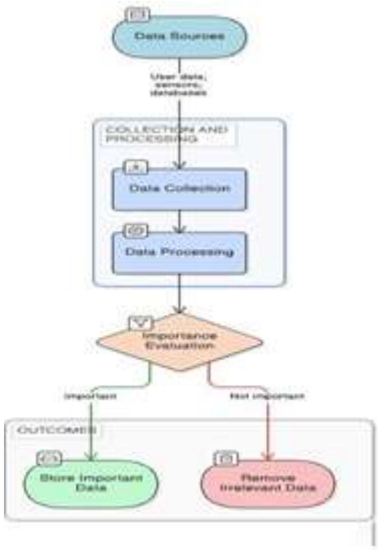

Fig. 1. Architecture of Digital Forgetting in AI Systems

This architecture shows how an AI system evaluates the importance of data and decides whether it should be stored or removed.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

VII. MATHEMATICAL MODEL

The score of every data item is computed as:
$Score=(w1\times Importance+w2\times Usage)\times e-\lambda t$

Explanation:
- Importance → relevance of data.
- Usage - number of visits.
- t → time elapsed
- λ → decay factor
- w1, w2 = weights to tune importance/use.

Behavior:
- High use/importance = high score.
- Low time score high.

This is to guarantee a smart decision on memory retention.

VIII. SYSTEM ARCHITECTURE

The system is composed of several layers that are collaborative:

- Input Layer - gets user data.
- Storage Layer- metadata data is stored.
- Processing Layer - compute score.
- Decision Layer - decides on keep/ remove.
- Output Layer- shows optimized data.

The multi-layered solution makes it efficient and scalable.

IX. TECHNIQUES FOR DIGITAL FORGETTING

A. Machine Unlearning
Machine unlearning allows AI models to forget training data, without necessarily re-creating the entire model.B. Memory Decay

B. Memory Decay
The importance of stored data fades away with time knowing that it is a technique. Data that is irrelevant are removed.

C. Data Pruning
To improve productivity, data pruning removes duplication or low value data in the datasets.D. Adaptive Learning

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

D. Adaptive Learning

In other AI systems, one of the processes is the upgrading of the knowledge base, or replacing the old information with the new one.

X. APPLICATIONS OF DIGITAL FORGETTIN

A. Recommendation Systems

In online platforms, AIs are used to recommend goods or content. The digital forgetting could help to make away with ancient user tastes.B. Healthcare

B. Healthcare

Medical AI devices must be able to maintain an up-to-date knowledge base. Removal of the ancient data improves the quality of diagnoses.C. Autonomous Vehicles

C. Autonomous Vehicles

Tremendous sensor data is generated by autopilot vehicles. Digital forgetting helps to erase unnecessary data and keep the appropriate driving patterns.D. Chatbots and Virtual Assistants.

D. Chatbots and Virtual Assistants

Digital forgetting helps in the deletion of sensitive discussions by the users in order to maintain privacy.

XI. IMPLEMENTATION (FORGETAI)

The ForgetAI is constructed to demonstrate how AI can forget meaningless information.
The back end is based on Node.js, Express, and MongoDB to store information such as significance, usage and time. It then uses the formula of forgetting to determine what data is to be retained and what is to be forgotten.

React is used to create the frontend where the user can view his or her data, scores, and graphs.
It further displays an analogy:

- Normal AI → stores all the data.
- ForgetAI → forgets less useful information.

This assists users to have a clear understanding of how forgetting enables AI to become faster and more effective.

XII. COMPARISON OF MEMORY APPROACHES

Table I. Comparison of AI Memory Systems

Feature	**Traditional AI Memory**	**Digital Forgetting**
Data Storage	Stores most data	Removes unnecessary data

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Efficiency	Slower over time	Faster processing
Adaptability	Uses outdated data	Updates knowledge
Privacy	Limited dat a deletion	Supports dat a removal
Storage	High storage usage	Optimized storage

XIII. DIGITAL FORGETTING PROCESS FLOW

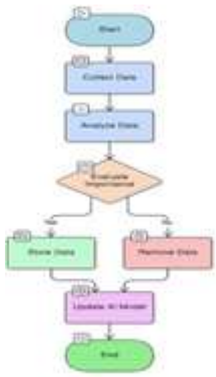

Fig. 3. Flowchart of Digital Forgetting

XIV. CHALLENGES

Adding digital forgetting is a good idea, yet it is also associated with a set of difficulties.

1. To begin with, it is hard to determine what data to be eliminated. In case of unintentionally deleting important data, it may decrease the precision of the AI system.
2. Second, deleting data may have an impact on the model functionality at times. Certain machine learning models can be highly reliant on training data and thus the removal of data could decrease stability or performance.
3. It remains a challenge to design good forgetting algorithms. The system should be made in such a way that the data is deleted safely and appropriately without damaging the overall results.

Simply put, the key challenges are:
A decision on the appropriate forgetting threshold.
- Not to lose valuable information.
- Maintaining the system as accurate and stable

XV. FUTURE SCOPE

In the Future, it is possible to make digital forgetting smarter and more automatic.

- AI SYSTEMS can learn by themselves what to retain and what to forget, without manual control. This will make the system quicker and efficient. Science is also trying to develop more effective methods of deleting data without any performance loss so that the system remains accurate even when it forgets.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

- AS DATA PRIVACY RULES are getting tighter, digital forgetting will also aid AI systems in preserving user data and adhering to legal requirements.

In simple terms, improvement in the future is going to consist of:

- SMARTER Artificial Intelligence that makes decisions on what to forget automatically.
- LEARNING-based systems that enhance forgetting with time.

Application in the real world of forgetting using digital.

XVI. CONCLUSION

Digital forgetting is an effective and essential concept of the development of modern AI systems, as it is based on the priority, filtration, and discarding of information inherent in human memory with time. Similar to humans dropping unnecessary or old information to ensure they can have more significant and better experiences, an AI system can enjoy the benefit of selective deletion of redundant information, low-value information, or outdated information. This allows not only to increase the computational efficiency but also to reduce storage overhead dramatically to allow systems to scale and not be overwhelmed by irrelevant information.

Additionally, digital forgetting is also important in improving user privacy and data security. Restricting sensitive or personal information stored in AI systems can bring the systems more in line with the ethical standards and data protection regulations. This is all the more important in a world where user data are created and processed in large quantities on a constant basis. Managed forgetting systems may help make AI systems compliant, responsible and trustworthy.

The other main strength is that of flexibility. The surrounding environments, users and patterns of data do keep on changing and AI systems must adapt to this. Models can forget old information and remain up to date, eliminate bias due to old data, and enhance the accuracy of their decisions. This results in more dynamic and context sensitive systems which are more reflective of realities at hand.

But there are no problems with the implementation of digital forgetting. Whether or not to forget, when to forget and how to make sure that essential information is not lost is a question of careful design and strong algorithms. Methods like decay functions, reinforcement learning, and memory prioritization strategies need to be improved and varying techniques created to attain the most effective operation.
To sum up, digital forgetting is not just a limitation but also a strategic asset. It is a move towards storing data to smart data, and a move towards more efficient, ethical, and intelligent AI systems. As the research of this field advances, in the construction of scalable, human-like artificial intelligence systems, the idea of digital forgetting will form the backbone of an artificial intelligence system that is capable of operating in the future.

XVII. AI MEMORY MODEL WITH SELECTIVE FORGETTING

Raw Data Sources
|
▼ Temporary Data Storage
|
▼

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

```
Machine Learning Model
          |
▼ Memory Evaluation
          |
   ┌──────┴──────┐
   ▼             ▼
Store Useful Data Digital Forgetting (Long Term Memory) (Remove Data)
          |
▼ Updated AI Model
```

Fig. 3. AI Memory Model

XVIII. EXPERIMENTAL RESULTS

The system was tested using sample data.
Results show:

- Memory reduced from 37 to 17 items
- Efficiency improved by ~54%

This demonstrates that digital forgetting reduces memory load while maintaining useful information.

REFERENCES

1. Y. Cao and J. Yang, "Towards making systems forget with machine unlearning," IEEE Symposium on Security and Privacy, 2015.
2. L. Bourtoule et al., "Machine unlearning," IEEE Symposium on Security and Privacy, 2021.
3. Z. Ma, Y. Liu, X. Liu, J. Liu, and K. Ren, "Learn to forget: Machine unlearning via neuron masking," IEEE Transactions on Dependable and Secure Computing, 2023.
4. W. Wang et al., "Machine unlearning via representation forgetting," IEEE Transactions on Information Forensics and Security, 2024.
5. Y. Liu, Z. Ma, X. Liu, J. Liu, and K. Ren, "Machine unlearning via neuron masking," IEEE Access, 2020.
6. J. Foster, S. Schoepf, and A. Brintrup, "Fast machine unlearning without retraining through selective synaptic dampening," IEEE Transactions on Neural Networks and Learning Systems, 2023.
7. Y. Liu, L. Xu, X. Yuan, C. Wang, and B. Li, "The right to be forgotten in federated learning," IEEE Transactions on Information Forensics and Security, 2022.
8. Z. Li, Y. Chen, and X. Liu, "Machine unlearning: A survey," IEEE Transactions on Artificial Intelligence, 2023.
9. A. Blanco-Justicia et al., "Digital forgetting in large language models: A survey," IEEE Transactions on Artificial Intelligence, 2025.
10. C. Li et al., "An overview of machine unlearning,"
11. IEEE Access, 2025.
12. I. Cevallos et al., "A systematic literature review of machine unlearning techniques in neural networks," IEEE Access, 2025.
13. J. Chen, W. Zhang, and Y. Wang, "Efficient machine unlearning via influence approximation," IEEE Transactions on Knowledge and Data Engineering, 2025.
14. H. Song, "Big data and AI integration for intelligent systems," IEEE Transactions on Industrial Informatics, 2022.
15. [N. Papernot et al., "Privacy preserving machine learning," IEEE Security and Privacy, 2018.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

16. K. Chaudhuri and C. Monteleoni, “Privacy preserving logistic regression,” IEEE Transactions on Information Theory, 2009.
17. B. Hitaj, G. Ateniese, and F. Perez-Cruz, “Deep models under the GAN attack,” IEEE Transactions on Dependable and Secure Computing, 2017.