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TOPICAL REVIEW

Emerging AI Technologies Inspiring the Next Generation of E-Textiles

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ABSTRACT The smart textile and wearables sector is looking towards advancing technologies to meet both industry, consumer and new emerging innovative textile application demands, within a fast paced textile industry. In parallel, inspiration based on the biological neural workings of the human brain is driving the next generation of Artificial Intelligence (AI). AI inspired hardware (neuromorphic computing) and software modules mimicking the processing capabilities and properties of neural networks and the human nervous system are taking shape. The textile sector needs to actively look at such emerging and new technologies, taking inspiration from their workings and processing methods in order to stimulate new and innovative embedded intelligence advancements in the e-textile world. This emerging next generation of AI is rapidly gaining interest across varying industries (textile, medical, automotive, aerospace, military). It brings the promise of new innovative applications enabled by low size, weight and processing power technologies. Such properties meet the need for enhanced performing integrated circuits (IC's) and complex machine learning algorithms. How such properties can inspire and drive advancements within the e-textiles sector needs to be considered. This paper will provide an insight into AI advancements in the e-textiles domain, before focusing specifically on the future vision and direction around the potential application of neuromorphic computing and spiking neural network inspired AI technologies within the textile sector. We investigate the core architectural elements of artificial neural networks, neuromorphic computing (2D and 3D structures) and how such neuroscience inspired technologies could impact and inspire change and new research developments within the e-textile sector.

INDEX TERMS Artificial intelligence, e-textiles, neural networks, neuromorphic computing.

I. INTRODUCTION

Smart clothing traditionally refers to a garment with the capability to enable/disable a function such as monitoring a person's physical condition [1], whereas an e-textile provides an added layer of intelligence such as connection to a peripheral or embedded electronic device into the garment or fabric, providing added value to the person that wears the item. Smart clothing leveraging embedded intelligent e-textiles with computational and memory capabilities are foreseen as the next big market mover in the Internet of things space. Demand for usable and wearable technology is constantly growing and the expected market traction has forecasted e-textiles growth from *2981 Million Dollars (2022) to 8508.1 Million Dollars (2028)* [2] [60]. Examples of such e-textiles applications include textile sensors for body biometric monitoring, wound monitoring or ECG analysis [3] [4]. During the COVID pandemic, there has been an increased interest in e-textile applications that focused on innovative smart personal protective equipment (PPE), such as smart face-masks [5].

Three generations of smart textiles have evolved over the years [6] (1) *1st generation* of smart textiles: there

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was little integration between the electronics and the textile (2) *2nd generation* of smart textiles: evolved with the adaptation of traditional textile fabrication methods to include additional functionality e.g. sewn in conductive thread into textiles and (3) *3rd generation* of smart textiles the integration of electronic sensing properties into textile materials.

What will the next generation of e-textiles and smart clothing look like. Advancements of ICT technologies AI intertwined with nanotechnology (*nano-textiles and wearable sensing nanomaterials*) are example key enabling drivers of the next generation of smarter and more advanced e-textiles, driving AI inspired computing fabrics.

AI at a very simplistic level aims to simulate human behaviour in a machine. We live in a world where increased levels of '*Big Data*' are being created. AI utilises machine learning algorithms (a branch of AI) to take this data and use artificial neural network (ANN) techniques to produce knowledge or useful predictive information quickly and accurately. Over the years, AI has developed advanced perspectives capable of AI image recognition and image generation [7]. Currently ANN is progressing and evolving towards spiking neural network (SNN) biologically inspired and more powerful models. Such AI SNN and neuromorphic computing core technologies, computational capabilities as well as their architectural structure bring the potential to inspire new and fresh innovations across many domains including the e-textile and smart wearables sector.

Wearable memory in a textile environment is also becoming a hot topical research area for further investigation. Rajan et al. highlight the advantages of wearable memories and computing devices (WMCs) and recent advances in nanotechnology and materials science [8], and how resistive switching devices (RSD) such as memristor RSD, threaded SD or wearable RSD are emerging as potential candidates for WMC applications [9], [10]. Such RSD wearable memories are foreseen to implement AI biologically inspired artificial neural networks. The link between WMC and the human brain could enable fast operation along with interface complexity, directly mapping continuous states available to biological systems.

Currently the textile sector has been experiencing a digital transformation predominately within its textile manufacturing processes and production industry, where AI-enabled technologies are being adopted for production line fabric inspection and defect detection, enhancing output quality [11]. Li et al. provide a survey of state of the art technological interventions that meet automatic fabric defect detection aligning to the industry 4.0 initiative [12], detailing traditional (statistical methods, structural methods, model based methods) as well as learning based methods (machine learning or deep learning). Intelligent clustering and classification techniques adopted and utilised in the textile's industry are summarised in [13], highlighting both supervised and unsupervised learning types supporting production planning, fabric fault detection, performance and predictive models.

In this paper we will examine in more detail AI ICT advancements focusing specifically on neuromorphic computing and spiking neural network AI, assessing their architectural structure, vision, capabilities and how these elements could be of relevance to inspire future research advancements in the e-textiles sector. Healthcare is emerging as one of the key sectors where e-textiles and new advances in AI driving embedded textile intelligence and on-body computation, can be leveraged and utilised in the near future both within a clinical environment such as a hospital and also support enhanced remote monitoring of patients from the comfort of their own home. Sethuraman et al. details a smart garment *MyWear* that monitors and collects physiological data (*muscle activity, stress levels and heart rate variations*) processing the data in the cloud and providing predictions to the user based on abnormalities detected [14]. Such e-textile applications and services utilising these AI technologies bring the added value of a more effective real time monitoring and analysis for varying health conditions such as cancer care, cardiovascular and neurological disorders, leading when required to early interventions as critical health concerns are detected. Elo et al. gathered feedback from a workshop of 50 participants focusing on the use of e-textiles to assist healthcare, rehabilitation and well-being, posing questions that focused on who could benefit from e-textiles and how could e-textiles be used [15]. Feedback obtained stated the potential beneficial uses of e-textiles linked to (1) Work environment (e.g. safety and ergonomics, radiation monitoring, well-being monitoring (2) Rehabilitation (e.g. neurological, mental health monitoring, speech and language) (3) Healthcare (e.g. home care, hospital care, pain relief) (4) Daily Life (e.g. safety, communications, emotions). The '*Internet of Smart Clothing*' [16] pushes the boundaries around smart garment intercommunication, their interaction with environmental objects and how they actively communicate with remote servers for the provision of advanced services. The next generation of smart clothing and e-textiles brings more intelligent embedded technological layers than before and hence has requirements for more flexible, modular, integrated, seamless and usable functionality to meet end user needs. The structure of this paper as detailed in Figure 1, provides an initial insight into current AI intelligence activities of relevance within the textile sector along with an example of such applications. The remainder of the paper provides a deeper dive into the key properties of spiking neural networks and neuromorphic computing, creating a mapping across to traditional functional technical properties of importance that are necessary to be considered for any new AI inspired e-textiles driven innovations. The paper is organized as follows: Section II details AI intelligence currently impacting the textile sector, highlighting the four core functional technical properties of importance to be considered linked to data flow communication and process methodology. Section III provides an insight into example

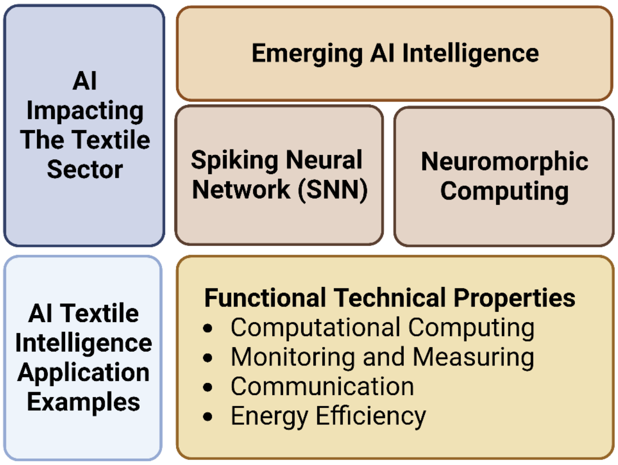

FIGURE 1. Structural and topical review elements in the paper.

use case AI e-textile intelligence. Section IV discusses the architectural properties of a spiking neural network with cross-reference to the four core technical functional properties and section V discusses the architectural properties of neuromorphic computing and their alignment to the four functional technical properties to provoke thought around how inspiration can be taken from these elements and actively feed into next generation of e-textiles. Section VI finalises the paper with a conclusion.

II. ARTIFICIAL INTELLIGENCE IMPACTING TEXTILE SECTOR

E-textile research domain experts, suppliers and manufacturers are starting to investigate at a deeper level the impact AI and machine learning technologies can have across varying sectors [17]. Digital transformation through the use of AI back propagation algorithmic neural network models are currently impacting the textile industry through the creation of a more sustainable digital supply chain and smart intelligent textile manufacturing optimization (production planning and operational process management) right through to fabric defect identification, pattern inspection analytics and much more [18], [19]. Sikka et al. provide an insight into the application of AI in textile manufacturing areas including yarn production, fabric production and dying production [20]. Such innovations have proven to boost productivity, enhance the percentage of yarn/fiber defects identified, as well as providing a safer working environment. How such enhanced and smart technologies can aid the textile industry towards a sustainable and circular economy is of high priority and gaining a substantial amount of attention [21]. Textile fabric based design software is also seeing the adoption and usage of AI based software tools in pattern design, making and cutting, providing a superior level of tools with inbuilt 3D visualisations features (3DCLO, Marvelous Designer) [22], [23].

The adoption and use of AI within fabric based textiles requires a structured and methodological process taking into account technical properties of importance along with the end user functional and form factors, as listed in Table 1.

All these elements directly relate to the data flow communication and processing methodology. In this paper we will adopt these elements in order to map across new AI technology properties to the textile domain within section IV and V. Currently within the healthcare medical sector such technical functional properties are applied and demonstrated through intelligent e-textiles for patient centric garment-based wearables [24]. Such considerations in the design and development enable the possibility to gather human monitored health related data sets such as Electromyography (EMG) or Electrocardiography (EKG) data-sets through textile based sensors in wearable garments. Such data collection type garments and textiles need to be adaptable to the user's needs for ease of use at varying levels. Through the active collection of these data-sets, this allows for the transmission, processing and extraction of key analysis and results for effective decision. This is aided through the development and implementation of intelligent algorithms.

TABLE 1. Technical properties to consider for embedded fabric based textile intelligence.

Technical property	Functional technical property consideration types
1	Computational considerations
2	Monitoring and measuring considerations
3	Communication considerations
4	Energy considerations

The use of AI based algorithms and techniques enables an era of intelligent textiles utilising real time and accurate data knowledge in dynamically changing healthcare monitoring type environments. When considering such embedded AI in a textile environment, there is a need to also look at the state of the art of current AI formal methods (e.g. data preparation, training etc) and how they must be advanced to adapt stemming key challenges and questions that will require further investigation and research as technology advances and emerges in this space.

One such example pushing the boundaries around the use of conductive threads and embedded smart wearable intelligence and functionality, Chan et al. were successful at their attempts to store data in fabric. Data is stored in bit strings on a magnetised smart fabric, where it is encoded as a positive or negative polarity (0 or 1) using the ferromagnetic properties of the conductive fibre. They successfully demonstrated an application utilising a shirt encoded with an image that is stored as a pass-code, once when scanned using a magnetometer and matches the predefined pattern allows a door to open in order to gain access by swiping the shirt's arm that holds the pass-code [25].

Further investigation and experimental research is required to identify what fabric-based AI algorithms could look like, how they could be developed and integrated in a functioning

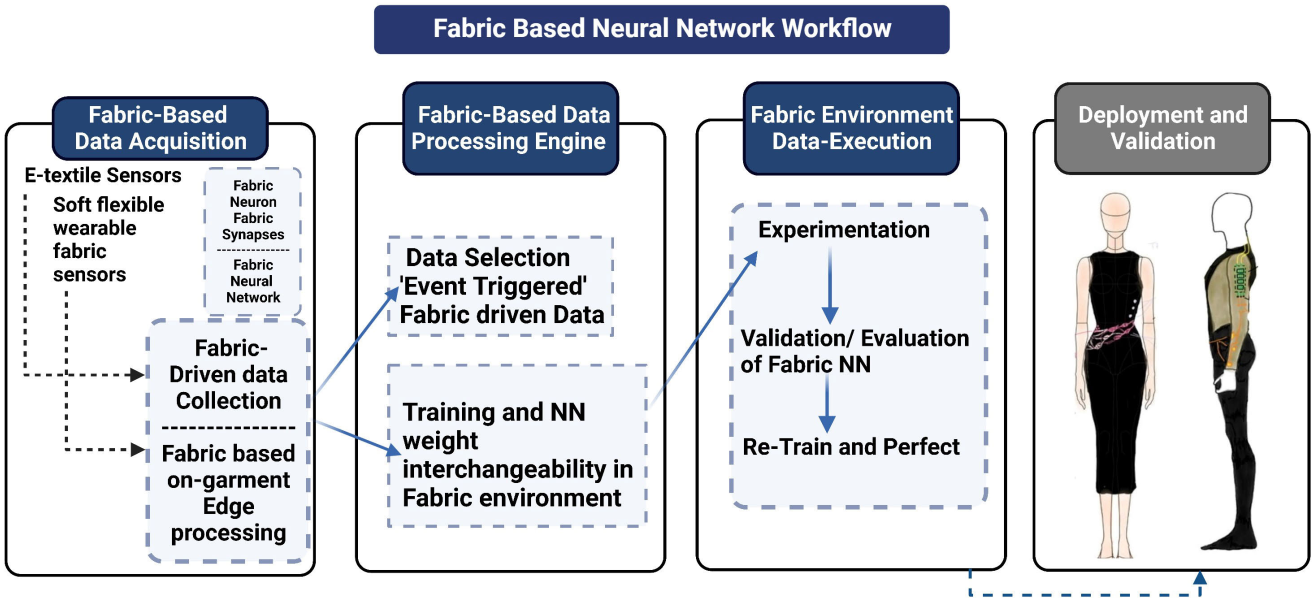

FIGURE 2. **Fabric based Neural Network Workflow.**

manner in the very core of a fabric and fibre environment. Not only will new fabric AI design fabrications begin to emerge, but also new fully fabric driven data acquisition and data processing driven approaches potentially adopting or inspired by new AI best practice, standards and methodologies. Key features of fabric-based AI algorithms need to consider during implementation speed (response time), processing capabilities, complexity/size and also learning. Figure 2 provides an overview of the key components for consideration for a textile driven AI workflow facilitating fabric based data acquisition, a data processing fabric-based engine, data execution in a fabric environment and also deployment. From an e-textiles point of view, each of these four AI pillars need further research and in-depth analysis to consider how such a workflow can operate and function in a textile fabric environment. From integrated intelligent textiles sensors in a fabric environment, how such data sources can be collected and processed need to be considered. The concept of a fabric neuron and fabric neural network embedded in a textile environment are actively being considered, so how can this support advanced data selection and fabric edge driven computation where fabric based algorithmic learning/training can be incorporated and executed in real time.

Other advancements and research linked to AI and textiles include Shi et al. [17] who provide a comprehensive review of advancements in Smart textile integrated microelectronic systems, highlighting the core properties of importance (1) flexibility allowing for effective drape on 3D curvilinear surface such as a human body and (2) structural transformation of textiles resulting in low fibre strain and fabric life cycle longevity. Loke et al. [26] convey a vision of moving from fibre devices to *fabric computers*, where the fabric fibers have inbuilt capability to perform sensory, storage, processing and powering capabilities providing a fabric based computing environment. Such a powerful fabric fibre based processing capability enables the execution of fabric based programs that can activate fiber sensors, processing and storing data within the fabric computer. Work has been ongoing around the development of such new fibres with specific focus on scalable processes using thermal drawing, melt spinning, coating to provide fibre structures that can house and deliver computing functionality [27], [28], [29]. Investigative methods into the digital fabrication of fibres is being researched where inbuilt functionality provides in-fibre storage programs, data storage, sensors and digital communication, such a fabrication structured process proposes uniform placement of discrete in-fibre electronic devices that will carry out such functionality. Researchers are actively thinking outside the box about new and potentially disruptive innovative ways to fuse AI with e-textiles moving away from the traditional textile world as we know it [30], [31]. This is sparking a renewed interest in this domain and shows promise of real impact across multiple sectors. The next section will provide an insight into two potential use case applications, demonstrating the potential for advancements in this area.

III. AI TEXTILE INTELLIGENCE APPLICATION EXAMPLES

Embedded AI intelligence in a fabric based environment has the potential to be applied across many sector based applications. Here we briefly provide two such examples in order to convey the possibilities of such an advanced fabric computing and fabric AI intelligence driven era, (1) the healthcare sector application space and (2) the unmanned aircraft/drone sector where textile driven drone control intelligence applications could be exploited.

A. HEALTHCARE AI SMART TEXTILE USE CASE

Smart garment applications can greatly contribute towards remote monitoring, where individual and personalised healthcare provides enhanced real time assessment and early intervention. Embedded seamless AI in a textile environment adds another layer of real time intelligent wearable point of care going beyond current state of the art. The application of AI intelligence in a fabric wearable environment bring the potential for enhanced quality of life for end users. Here we provide two such conceptual end user-centric scenario examples.

Healthcare Use Case: Aisling is concerned about getting a variant of COVID-19 and is looking for a new means to be able to monitor and track her general health without it impacting on her daily activities. Aisling purchased an AI monitoring package (*textile sensors and Fabric AI patch intelligence*) that can be fitted in a modular manner into her latest modular clothing garment. Aisling now has embedded AI in her everyday clothing and can monitor her breathing and temperature, analyse the data in real time and be alerted about abnormalities that occur, allowing her to respond in an efficient manner, detect symptoms early, take a COVID test and restrict her movements if needs be.

B. TEXTILE-DRIVEN DRONE CONTROL USE CASE

The application of e-textiles across multiple domains and sectors is gaining traction. New innovative ideas extending beyond the norm of healthcare are starting to be considered and emerging. Advances in fabric based AI intelligence open the opportunity to extend applications of e-textiles fusing non-traditional techniques and new technologies. An example of one such area is the application and use of a based fabric textile intelligence with unmanned Ariel vehicles (UAV). The following provides an example use case for consideration.

Taking a modular designed dynamic field programmable or Fabric AI-driven smart garment with intelligent embedded control logic functionality [32], [33] opens up opportunities towards the use of such a smart garment as a control device of the UAV's based on human control activated movements linked to the smart garment triggering smart textile sensors as actuators directing the movement and control of the UAV. Such fabric AI driven haptic wearable devices can have multiple applications for varying devices, providing a more seamless embedded control options for end users. This has numerous innovative applications in construction, defence and more.

The next two sections of the paper will focus on emerging AI technologies (1) spiking neural networks (SNN) and (2) neuromorphic computing. We will delve into the technological and architectural aspects of importance, aligning them where relevant to the four core functional technical properties identified in section II table 1, that are required to be taken into account when considering embedded AI technical functionality in a fabric driven e-textile environment.

IV. SPIKING NEURAL NETWORK PROPERTIES INSPIRING NEXT GENERATION OF E-TEXTILES

Artificial neural networks are seeing the emergence of new SNN technologies. SNN simulates functionality using electronics components replicating and mimicking human brain biological workings of neurons, synapses and neural networks. Core architectural properties of an SNN include

- Neurons that emit a spike once a set threshold has been met.
- Learning in the neural network is completed by altering the synaptic weight. Random weight change algorithm is one of the most adopted and simple algorithms used during the learning phase. For this algorithm the correct output is known and the error increased or decreased as required.
- Results obtained depends on the neuron spiking activity and also the neural node inputs.

Taherkhani et al. detail and explain a single neuron level [34], giving 1D neuron model examples such as Leaky integrate and fire (LIF) [35], the Spike Response Model (SRM) as well as more complex and biologically feasible artificial neurons such as the Hodgkin and Huxley model [36]. We will now assess the core computational, monitoring/measurements, communications and energy of such SNN, highlighting structural and processing paradigms inspired by the human brain and the potential they could bring to the e-textiles domain. Figure 2 details the adoption of this data flow communication and processing technology methodology to the e-textile domain, highlighting a fabric based workflow of relevance towards the implementation, validation and deployment of fabric driven AI (neural network) intelligent e-textile wearables. In the next section we will delve into key SNN computational technical elements, highlighting core current research textile component advancements of importance.

A. SPIKING NEURAL NETWORK COMPUTATIONAL CONSIDERATIONS

Data acquisition refers to the methodology and process of acquiring data and performing analysis in order to interpret it. This involves the use of varying techniques and tools used to sample data, convert the data into a format that can in turn be used for further analysis and processing. From a neural network point of view, we will now investigate further the main computational elements with a focus on highlighting architectural aspects of importance for consideration in a textile environment (1) *Artificial fabric neurons* (2) *Artificial fabric synapses* (3) *Artificial fabric neural networks* required to perform data acquisition and processing and the potential for adoption into a fabric environment.

1) E-TEXTILE ARTIFICIAL FABRIC NEURON

Neurons are the core building blocks of neural networks. The workings of a neuron include synapses represented by weights, a threshold and an output spike that in turn resets the neuron. Each neuron has a membrane potential.

This membrane potential is the equivalent of a voltage and when that voltage passes a defined threshold a spike (*or action potential*) is emitted and hence this generated spike is the method by which one neuron communicates to another neuron in a SNN, through information encoded in the frequency of the spikes. Taking these aspects, how can we begin to consider a fabric based neuron, its workings to replicate not only an individual neuron's functionality but having the capability to be extended to implement multiple interconnected neural nodes in a fabric environment. To work towards such a goal, we have to delve into the artificial electronic neuron representations currently defined and that could inspire future fabric based neural implementations. Here we will consider the Leaky integrate and Fire Model and the Hodgkin and Huxley Model. Further enhancements to these models and other models exist, but this is outside the scope of this paper.

2) LEAKY INTEGRATE AND FIRE MODEL (LIF)

The most simplistic model of a neuron is the *Leaky Integrate and Fire neuron* artificial electronic circuit based on the logic that if the spike (driving current) goes beyond the defined threshold, then the neuron emits its own spike and resets. The model operates based on a resistor and capacitor (RC circuit) driven by a current I(t) demonstrated in [Fig 3].

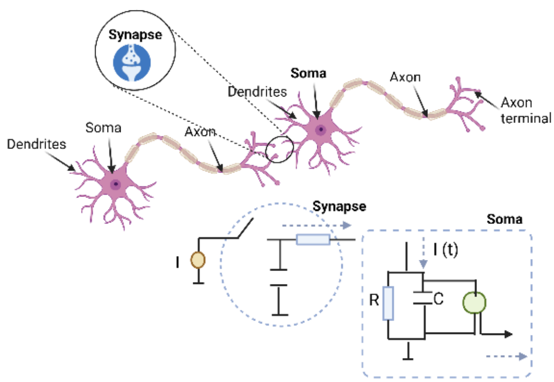

FIGURE 3. Simple Integrate and Fire artificial (RC) neural node.

Limitations of the LIF model is that no memory of spiking activity is retained as the membrane potential is reset after each spike. We need to consider how such a LIF model could be replicated to produce an event driven spiking neuron in a fabric environment leveraging the leaky integrate and fire neuron model. The following details current textile component based research ongoing of relevance when considering the creation of a LIF fabric neuron.

- *Soft textile based resistors* can be fabricated using conductive thread, typically using a zigzag sewing machine stitch. Depending on the conductive thread (resistance level, ohms per metre) as well as the density of the zigzag stitch utilised, this dictates the overall resistance level when choosing such a textile resistor to create.
- Ongoing research is active around the development of *textile based capacitors* [37]. Blecha and Moravcova investigate methods for the capacity increasing of textile capacitors for planar and sandwich type textile capacitors using hybrid conductive threads and conductive textiles [38]
- Additional embedded *textile transistor gated circuitry* is required in order to implement the threshold level *Vth* for the membrane potential, when this threshold has been reached this produces an action potential spike. Bonfiglio et al. detail an organic field-effect transistor that is realized on a flexible film that can be applied, after the assembly, on textiles [39]. Carey et al. showcase a fully inkjet-printed 2D-material active heterostructures with graphene and hexagonal-boron nitride (h-BN) inks, which are used to fabricate an inkjet-printed flexible and washable field-effect transistors on textile [40]. Such advancements in textile based FET's bring the capability to incorporate textile threshold level gates, enabling the possibility of varying threshold levels for the various neural nodes in a fabric spiking neural network.
- Experimental research has also been ongoing into the development of wearable fabric Brain enabling on-garment edge-based sensor data processing inspired by SNN architectural techniques and LIF model [41]. This wearable smart sleeve prototype developed and tested a 3 input, 2 hidden layer, 2 output wearable SNN connected to fabric pressure sensors in the garment, capable of classifying the haptic sensing coming from the textile pressure sensors in the garment's sleeve at key placement points (base thumb, mid-forearm and lower elbow). The wearable fabric brain can compute in real time in a fabric environment, which part of the arm's smart sleeve has been touched. Such advancements will open up options and new methods to work towards functional fabric based neural nodes based on an RC circuit and LIF model, capable of processing event spike driven activity replicating a neural node, that can be extended into a basic working event driven spiking neural network.

3) HODGKIN AND HUXLEY

neuron model is a more complex model to replicate the generation of an action potential of a neural node. The model can describe the time behaviour of the membrane potential and currents through potassium (K) and sodium (Na) channels using differential equations as seen in [Fig 4]. They were able to observe the generation of action potential as well as the refractory period [42]. In this circuit the capacitor is representative of the cell membrane, the circuit has variable resistors that represent the voltage-dependent K+ and Na+ conductance's and there is also a fixed resistor representing the voltage-independent leakage conductance. This model has three power batteries for the reverse potentials for the corresponding conductance's.

Generation of this model in a fabric environment would require the textile resistor and capacitor, as well as the requirement for a variable resistor interconnected using conductive thread. To date, variable textile resistors have been created in the form of fabric based potentiometers. Such fabric potentiometers contain a conductive wiper function as well as a resistive track where its ends has measurement points included. The conductive wiper acts as a means to set and measure a variable resistance through adjustment of the sliding wiper. Lindrupsen details and demonstrate a zipper based potentiometer [43]. Other variable resistance elements that could be considered to produce such a variable resistor include Eeonyx Stretchy Variable Resistance Sensor Fabric (*Adafruit*) that can be utilised to make soft sensors that are required to be movable and adaptable. Such stretch fabric sensors using stretchable conductive fabric enables changes in resistance when stress is applied. Further research is required into how textile and fabric based variable resistance can be leveraged and potentially be utilised in the design of a fabric neural node. Key textile components are

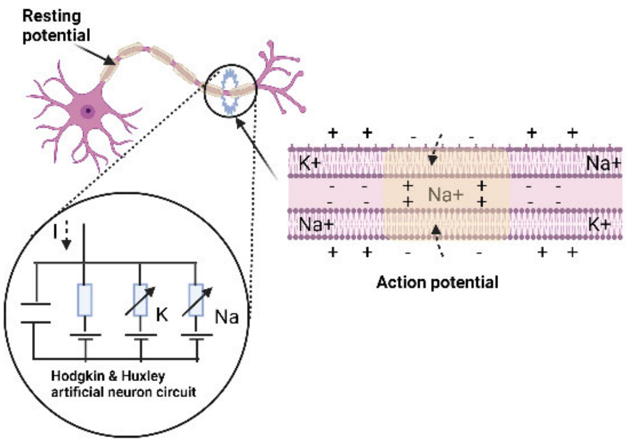

FIGURE 4. Hodgkin and Huxley electronic Artificial neural node.

in existence to enable the creation of a fabric based Hodgkin Neural Node, how such elements can come together from a design perspective to produce a working neural node is the key challenge here in order to produce a working Hodgkin and Huxley fabric neural node.

4) E-TEXTILE ARTIFICIAL FABRIC SYNAPSE

Current learning in SNN are dependent on the capability to alter and interchange the synapse weights for each of the neural network nodes. When a neuron threshold is reached, it fires and produces an action potential. This is a result of the sum of excitatory and inhibitory potentials and these are connected to the neuron through the synapse. We refer to the synapse as a synaptic weight. This is the strength of a connection between two nodes in a neural network. Park et al. investigated yarn coated with reduced graphene oxide (RGO) to produce two-terminal memristor-based artificial synapses suitable for use in wearable neuromorphic computing systems [44]. They successfully fabricated an artificial synapse using reduced graphene oxide (RGO) coated conductive yarns capable of emulating synaptic functions even when bending was endured. The author believes the yarn based artificial synapse created is a potential good candidate for future wearable neuromorphic systems. Ham et al. researched the design and development of a one-dimensional organic artificial multi-synapses enabling electronic textile neural network for wearable neuromorphic applications, where the multi-synapses consisting of ferroelectric organic transistors fabricated on a silver (Ag) wire [45].

To replicate a SNN in a fabric environment we need to consider the functionality required for the fabric synapse and how to embed this in a workable manner into a textile environment. As the weight influences the firing of a neuron, in a SNN, at a basic level this can be replicated by embedding the option to be able to connect and interchange from one conductive thread-based resistor in a fabric environment to another conductive thread resistor. Such textile resistors can in turn be utilized as synaptic fabric-based weights. Further advancements with the introduction of memristors as synaptic weights are emerging and need to be considered from a fabric synapse implementation point of view, these will be covered in section V neuromorphic computing properties.

TABLE 2. Types of Neural Network more relevant to SNN's.

SNN Type	Data Flow	Memory	Prediction	Weights
$FeedForward$	Input to Output	No Memory	Poor	Weight matrix inputs, produces output
$Recurrent$	Looping Information cycles	Has Memory-learns	Good	Weights applied current and previous inputs

5) E-TEXTILE ARTIFICIAL FABRIC SPIKING NEURAL NETWORK

There are multiple types of neural network's perceptron, multilayered perceptron, feedforward, recurrent, fully connected, Convolution, Radial Basis Functional, Long Short-Term Memory (LSTM), Sequence to Sequence Models and Modular Neural Network. Table 2 provides an overview of a feedforward and recurrent neural network properties of relevance when considering a SNN type to adopt and conform to [46], [47], [48]. When designing an embedded neural network in a fabric environment key fabric and end user properties need to be accounted for including aesthetics, durability, comfort and maintenance. Based on the overall size of the SNN and the number of hidden layers it incorporates, this deciphers the number of textile artificial neural nodes, synapse interconnections and interconnected fabric multilayers required. We can then begin to investigate the best possible design, layout and functionality integration methods around how to accommodate and embed into a fabric environment.

B. SPIKING NEURAL NETWORK MONITORING AND MEASURING CONSIDERATIONS

A SNN can learn by supervised learning, where an input and an output variable and the algorithmic computation within the neural network learns from a training dataset. Once an acceptable level of performance is achieved, the learning stops. An unsupervised method in comparison has input variables but no output variables that are used to support training and learning of the neural network. Pfeiffer and Pfeil present an overview of the varying training methods for SNN's such as conventional deep networks [49], constrained training, spiking variants of back-propagation and variants of Spike time dependant plasticity (STDP) in order to categorise SNN training methods and also highlight their advantages and disadvantages. Creating such a training or learning process in a fabric e-textile is a challenge that has not yet been achieved. The use of nanotech is the obvious initial best approach to attempt to embed such a learning element into an intelligent fabric garment.

Depending on the structure of a SNN, this identifies its classification. For this paper we will focus on a fully connected multi-layer neural network. Such a multilayered Spiking neural network consists of multiple layers of artificial neural nodes (usually has three or more layers and utilizes a nonlinear activation function). From a design perspective in a fabric environment once we have identified the core textile components required to implement a working neural node as well as a functional method for interchangeable synaptic weights, the next step is to progress towards the identification of a most practical and feasible fabric-driven design in order to incorporate multi-layers, their interconnections and how to be capable of validating and modifying during the execution phase.

Several layers of fabric woven and stacked produces a multi-layer fabric, secured together with connecting yarns in a third (Z direction) dimension. Such woven fabrication techniques along with layered and interwoven fabric manipulations are design options which need to be assessed to identify suitable and best practice design for the development of SNN technical textiles as demonstrated in [Fig 5]. Weaving multiple layers in a fabric provide the opportunity to embed neural network nodes and interconnected neural networks in an embedded fabric environment. Research into the best approach, the best methodology to adopt and also core components and their re-usability still remain under investigation, but as textile components and intelligence along with nanotechnology advances, new opportunities are emerging pushing towards this vision of a Fabric AI Driven intelligence. In section V we will delve a little further into 2D/3D stacked layered techniques, taking inspiration from neuromorphic computing and advancements here.

C. SPIKING NEURAL NETWORK COMMUNICATION CONSIDERATIONS

SNN drives the adoption of brain-inspired computing, providing not only fast but also a substantial amount of event-driven data processing. An SNN neural computation and communication is defined through the generation of spikes enabling neurons to communication from one to another via such

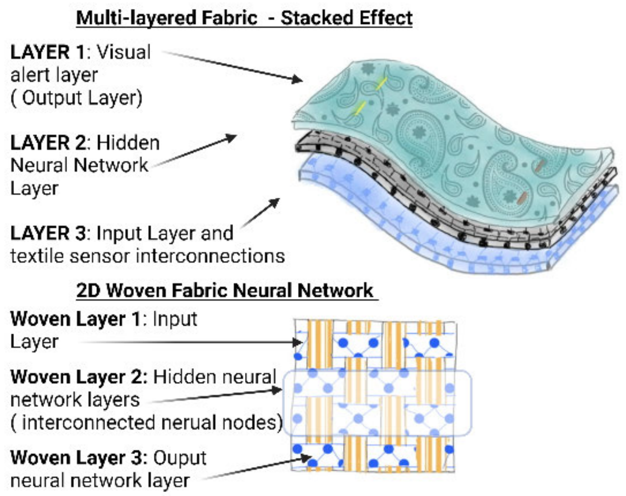

FIGURE 5. Multilayered conceptual design approaches inspired by stacked neural networks.

triggered spikes. Research is ongoing around the types of neuronal information encodings. Auge et al. summarise the signal encoding schemes for a spiking neural network [50]. Neuronal encoding and decoding is the information and communication process where for example an external variable or stimulus triggers neural activity within the brain. Such stimuli (e.g. touch stimuli) produce varying neural activity patterns in the brain. Zeldenrust et al. provides an overview of neural coding with bursts and new methods for their analysis [51]. Comsa et al. introduce spiking autoencoders with temporal coding and pulses, trained using backpropagation to store and reconstruct images with high fidelity from compact representations [52].

Classification of the spike train pattern and what this means, enables active decoding of the pattern. One such example is the classification of spike train through active matching of the spike train patterns to templates. Such a template would be a set word, meaning or result. Within an e-textile world neural information encoding, decoding and the creation and validation of potential *Fabric SNN classification templates* mapping to external sensing embedded textile sensors linked to fabric based neural networks, could enable the communication and processing of fabric based SNN encoding. Such Fabric SNN classification templates could correspond to an alert notification raising awareness around a critical health monitoring scenario where such a template could be used in conjunction with a SNN fabric Smart garment to assess the health status and provide feedback to the wearer based on the use of such classification templates to raise alerts to the wearer as required. Core to the fundamental working of a SNN is the manner in which the network nodes interconnect and how information flows and communication between the nodes is enabled. Multiple artificial neural network types exist. Guo et al. provides a comparative overview of neural coding in a spiking neural network with in-depth detail on rate coding, time-to-first spike (TTFS) coding, phase

TABLE 3. Neuronal Information Encoding Types.

Coding Type	Details
$RateCoding$	Rate of spikes in a set time interval.Can be used at single neuron level or interpretation spike trains.
$BinaryCoding$	A neuron is active or inactive in a set time interval.It fires 1 or more spikes within that timeframe.
$Timetofirstspikecoding$	Method is used to encode information for fast responses (in milliseconds). it is based on first-spike patterns).
$FullyTemporalcoding$	Precise timing of all spikes generated are part of the encoding. Timings are important.
$PhaseCoding$	Convert inputs into binary representations (eg a '1' equals a spike generated. Information is added by assigning different weights to each bit represented in the phase
$BurstCoding$	A burst of Spikes (Short and High frequency of Train of spikes. Assessment of the number of pattern of spikes in a burst coding
$Latencycoding$	Number of spikes is not the priority, instead the time between an event and when the first spike triggers is important. Stimulus is encoded based on a rank-order where neurons in a group generate their first spikes

coding, and burst coding [53]. Table 2 provides a substantial list of the types of neuronal information encoding techniques utilised to-date for consideration. It highlights their key elements for consideration when investigating the potential for fabric-driven SNN neuronal encoding and decoding.

D. SPIKING NEURAL NETWORK ENERGY CONSIDERATIONS

Spiking neural networks bring the promise of enhanced energy efficiency. As an SNN is a dynamic system, this suits more dynamically driven processes and applications. Research is ongoing to investigate how to effectively lower synaptic operations and hence the computational performance of the neural network. Sorbaro et al. focus on the optimization of energy consumption of SNN for neuromorphic applications through a hybrid training strategy that also accounts for energy cost stemming from the networks computations [54]. From a structure and architectural point of view SNN have typically fewer neural nodes than more traditional artificial neural networks along with the fact that SNN can implement *node connection pruning* in order to reduce processing power and improve overall the working functionality and energy efficiency of the SNN as demonstrated in [Fig 6]. By removing select unnecessary weights in the model this enables model compression while maintaining the core functionality of the neural network as conveyed in [Fig 6].

Shi et al. develop a pruning method for SNNs by exploiting the output firing characteristics of neurons, which can be applied during network training [55]. Rathi et al. detail the process of pruning STDP-based connections as well as

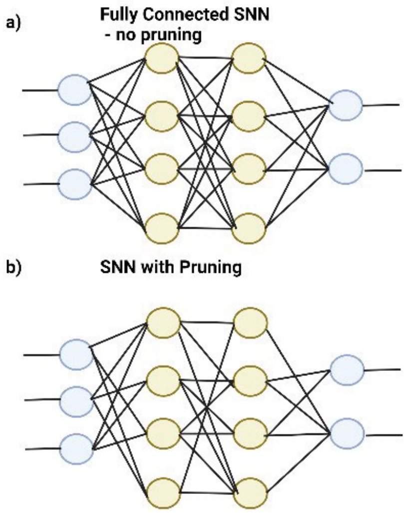

FIGURE 6. Difference conveying no pruning in SNN versus pruning in SNN.

quantizing the weights of critical synapses at regular intervals during the training process [56]. They test the network for digit recognition (Modified National Institute of Standards and Technology (MNIST) dataset) [20] and also completed an image recognition test based on images coming from the Caltech 101 dataset. They validate a classification accuracy of *90.1* percent and show an improvement in energy efficiency. When implementing a SNN in a textile environment, the capability to be able to disconnect and reconnect fabric neural nodes needs to be considered in order to be able to prune the Fabric SNN (*fabric node pruning*) in an efficient manner enhancing the fabric SNN energy operational functionality. From a computational point of view the SNN has the capability to operate more quickly due to the neurons sending spike impulses. As SNN's adopt temporal information retrieval this increases the overall processing time and productivity and hence has a very positive end impact on energy consumption in the SNN. The next section provides detail on neuromorphic computing and key architectural elements of importance for consideration.

V. NEUROMORPHIC COMPUTING PROPERTIES INSPIRING NEXT GENERATION OF E-TEXTILES

Neuromorphic computing concept originated in the 1980's, inspired by computer science, mathematics and bio-inspired models of neural network technologies. This emerging interdisciplinary research field has the potential to be disruptive, moving away from traditional computing methods and architectural implementations, such as the von Neumann architectural approach where separate memory and computing capabilities reside in order to meet high computational power requirements. Instead neuromorphic computing will focus on the implementation of more centralized and combined memory functionality. Such inspiration coming from the working of the human brain paves the way for new and more fault tolerant layered and parallel architectural designs and layouts.

TABLE 4. Taking Inspiration from SNN and neuromorphic advancements, highlighting key considerations to feed into future e-textile neural network research and prototypes.

Human Brain- SNN properties/Neuromorphic Computing Properties	Inspired E-textiles Considerations
Synapse/Memristor: component that regulates electric current flow remembering the previous current flow through.	How to represent weights in a fabric environment to simulate synapse interconnections between fabric-based neurons. Conductive thread-based resistors, surface mount devices or nanodevices in a fabric environment to simulate the workings of the synapse weights. Interchangeability of these weights in a fabric environment need to be considered and generation of a new method and fabric-based process around how to design, develop and validate. How to embed in a workable manner a wearable memory aspect in a fabric environment, in a seamless functioning manner. What would a fabric based memristor look like, how could this be completed and validated in a fabric environment.
Soma/Neuristor: Device to capture the properties of a neuron, Spike or impulse generation when threshold reached.	Replication of a Neuron in a fabric environment.Take inspiration from current electronic artificial neurons (LIF, Hodgkin Huxley). Considerations around how to create textile and fabric-based components to replace hard component elements (conductive thread-based resistors, textile-based capacitors). The aim being to investigate the most suitable way to create a working fabric neuron but with limited hard components instead using textile versions.
Axon/Circuit interconnections and signal conditioning.	In order to maintain the focus on a textile-based implementation, the use of conductive thread (embroidered conductive thread neuron interconnections design pattern) as a means to easily reproduce and create such fabric neuron interconnections.
Dendrite/3D architectural design implementation, pattern detection and sub threshold filtering.	Taking inspiration from the 3D architectural design used in Neuromorphic computing, can this motivate and inspire new 3D fabric manipulation and 3D fabric layering type designs in a garment structure, to embed and interconnect such fabric driven neural network functionality.
Fan In, Fan Out/Implemented using crossbar array, but this has limitations with regard to scaling. Higher radix interconnections are being considered. (Loihi2 provides faster and higher radix interfaces).	Conductive thread, with insulation bridges to eliminate short circuits in a fabric environment, can be utilized to embed such a crossbar array design in a textile environment. Depending on the type of synapse utilized (conductive thread resistor, SMD resistor, memristor or other) a physical connection to this synapse type will need to be considered to assess the best approach in order to interconnect to the fabric-based crossbar array.

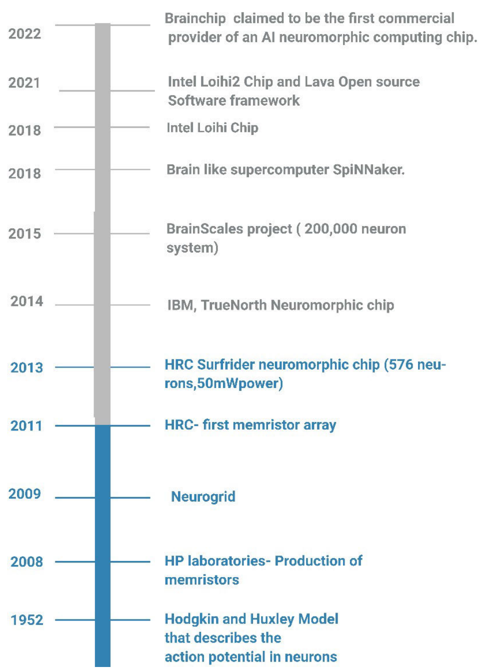

FIGURE 7. Timeline of technological advancements in Neuromorphic Computing.

In order to understand what aspects of neuromorphic computing can inspire innovative advancements in the next generation of smart e-textiles and on-garment edge based intelligence, we will first highlight the core architectural elements of importance within neuromorphic computing and assess their potential within an e-textiles domain. Neuromorphic computing core architecture is based on the concept of communicating through event driven spikes generated through simple processing structures represented by synapses and neurons.

Ongoing research is pushing the production possibilities using complementary metal oxide semiconductor (CMOS) technology to develop neuromorphic spiking neural network hardware implementations [57], [58], [59]. Key properties such as *size, weight, low power consumption, and modular design (scalability)* are dominating the research areas of focus linked to such technologies. Advancements in CMOS technology has been a key enabler towards the design and development of smaller and more energy efficient systems, hence providing the capability to mass produce on a larger scale. Such technology combined with advanced machine learning techniques has directly lead to the simulation and implementation of silicon based neurons, otherwise defined as neuromorphic computing.

Figure 7 highlights neuromorphic computing advancements over time, with *Brainchip* (https://brainchip.com/) announcement in 2022 claiming to be the world's first commercial producer of a Neuromorphic AI processor '*Akida*' that has the capability to mimic the working of the human brain and process data with high precision and energy efficiency. Akida, an event-based AI neural processor, features *1.2 million neurons and 10 billion synapses*. The following subsections will delve into the key neuromorphic computing architectural properties of importance.

A. NEUROMORPHIC COMPUTING COMPUTATIONAL CONSIDERATIONS

1) CROSSBAR ARRAY ARCHITECTURAL PROPERTIES

As neuromorphic computing moves away from the traditional Von Neumenn architecture towards a more focused in-memory computational architecture, the processing occurs inside the memory functionality elements, hence reducing data transfer time and energy. Hardware architectural design considerations need to take into account (1) *synapse interconnections between neural nodes* and (2) *how this can be implemented in order to complete a fully connected neural network*. Key to neuromorphic computing architectural design is the crossbar array structure. From a hardware design perspective, the crossbar array architecture has been adopted in neuromorphic computing in order to implement a full complement of interconnections required to meet the neural network structure requirements.

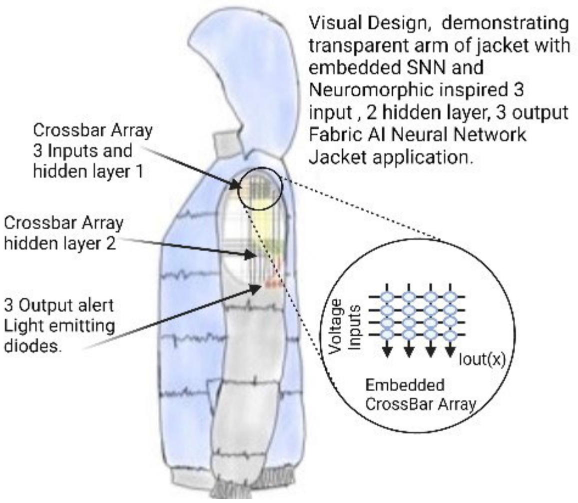

FIGURE 8. Conceptual Jacket design with embedded neural network using crossbar array architectural design.

- The crossbar array architecture includes a number of rows (word lines) and columns (bit lines) with memory devices interconnected between both the row and column.
- Advancements have been made through the development of resistive memory devices known as memristors (*one transistor and 1 resistor combination*). The operational functionality of the crossbar array is based on input current (*voltage pulse*) to selected rows which in turn activates selected columns via a voltage pulse, depending on the activation of varying cells in the crossbar array. For active cells in a particular row/column vertical line in the crossbar array, the sum of currents equals the output current, calculated using Ohms law and Kirchhoff's law.

Research into memristor crossbar arrays for brain inspired computing neural networking has been investigated [60]. Kim et al. report a 64 × 64 passive crossbar circuit that demonstrates approximately *99* percent non-volatile metal-oxide memristors, enabling the active storing of large neural network models on neuromorphic chips [61].

From a functionality and design perspective, how can inspiration be taken and mapped to an e-textiles fabric environment in order to progress towards an embedded neural network. The crossbar row/column structure design is a key element to consider, how can this architectural design be accommodated in a fabric material in order to recreate such a neural network as demonstrated in [Fig 8]. Such a visual in [Fig 8], demonstrates a fabric AI jacket with embedded crossbar array architectural intelligence with a 3 input, 2 hidden layered crossbar arrays and 3 output neural network application. Can embroidery based techniques and patterns using conductive thread, fabric tape or embedded woven conductive elements into a fabric environment be experimented with in order to recreate such a crossbar array type architectural structure in a fabric material. This is a key design element for further exploration and research.

B. NEUROMORPHIC COMPUTING MONITORING/MEASURING CONSIDERATIONS

Memristors also known as resistive switching random access memory devices that have the capability to change their resistance state and act as non-volatile memories for embedded memory based devices are showing promise in the neuromorphic world as key components to implement high-density memory. Properties of memristors include small device/high density integration, low power, high speed and highly scalable [62]. New research is focusing on the potential to enable controls for resistive filament switching in synapse applications, as well as further investigation around varying memristor materials for artificial synapses with specific focus on the synaptic behaviours of organic materials, 2D materials, emerging materials (*halide perovskites*) and low-dimensional materials [63]. The memristor is very suitable for analog based circuits as well as hardware multi-state neuromorphic applications due to its high and low resistance state. Interconnections between the neural nodes in the human brain have a joint strength represented by the synapse.

Memristive synapses are ideal candidates to create an artificial synaptic device, helping it mimic interconnection strengths between artificial neural nodes. A core requirement is the need to enable and alter resistance states. When we consider fabric smart material, how wearable memory can be incorporated into a fabric environment is a key element that requires extensive investigation and research. Taking inspiration from memristor-based analog memory circuits, what properties and elements need to be considered when considering the link between fabric materials and the application functionality. Analog memristors exhibit a gradual change

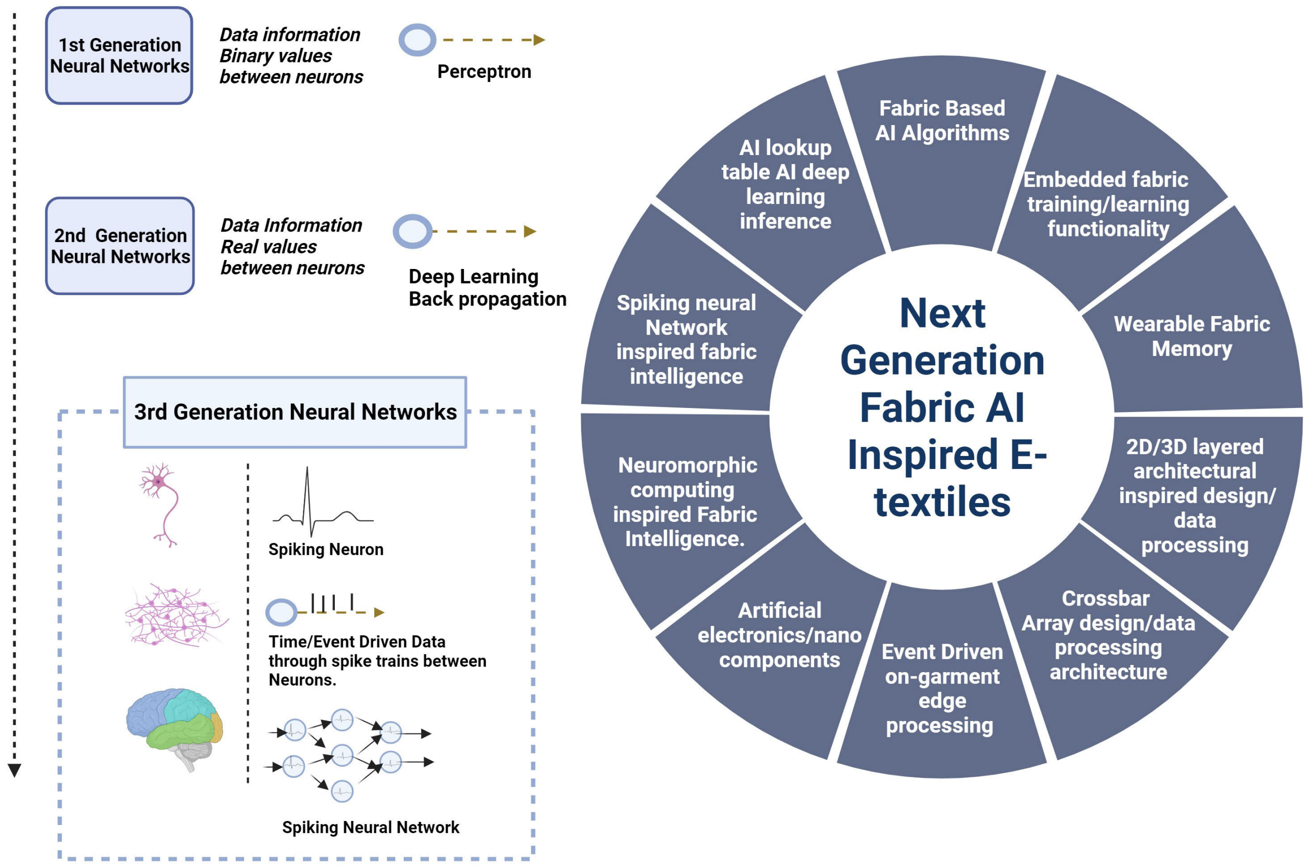

FIGURE 9. Core building modules and emerging technologies that are contributing towards the next smart textile's generation, incorporating Fabric AI inspired e-textiles.

in resistance and hence are more suitable for analog circuits and neuromorphic system applications. Bi-stable memristors act as binary memory/switches and digital logic circuits. Multi-state memistors are used as multi-bit memories, reconfigurable analog circuits, and neuromorphic circuits [64]. Researchers have implemented a method of weaving flexible computer memory into garments. This flexible memory is woven together using strands of copper and copper-oxide wires. Liu et al. demonstrate advanced research into the development of a *textile memristor* using a robust fibre through an electric field assembly method that weaves the fibres into a scalable textile memristor [65]. This exciting research era will see advances through the fusion of nanotechnology level memristor devices and e-textiles embedded AI intelligence.

C. NEUROMORPHIC COMPUTING COMMUNICATIONS AND ENERGY CONSIDERATIONS

Building on the crossbar array design, neuromorphic chip advancements look to implement energy efficient lower power consumption architectures supporting the required precision communication. In order to accomplish this research is ongoing around the design and development of smaller and multiple arrays. Such multiple arrays are emerging as either having a lateral 2D layout or a 3D vertical stacking layout. Circuit designs are required to be efficient in order to enable data flow between each layer in such 3D passive arrays. 3D memristive neural networks are taking inspiration from string stacking for 3D NAND flash (Xia et al.).

From a design perspective when considering how to embed a multilayered neural network in a fabric environment, it is vital to consider key properties of the fabric as well as key design and usability functionality requirements for end users. We already touched on possible layered and woven conceptual design layout approaches as seen in [Fig 5], but if adopting a 3D stacked layered fabric approach, how we can interconnect the layered neural node connections also need to be considered. How do we interconnect from one fabric layer to another fabric layer in an energy efficient, low power and reduced size capacity to ensure a high operational standard for the fabric based neural network. A modular fabric design-based approach with inter-changeable neural nodes and hidden neural layers may prove to be a more suitable option availing of the capability to interconnect, remove and replace neural nodes using for example snap connectors or other connector method options as described in [66].

VI. CONCLUSION

It's evident that AI driven technology advancements are moving at a rapid pace. Vast research stemming from architecturally inspired specification and design properties of SNN and neuromorphic computing provide valuable inspiration towards new techniques, methodologies and designs that can be applied across to drive emerging innovations in the e-textiles domain. This paper has delved into key architectural properties of SNN (*artificial neurons and synapses*) as well as neuromorphic computing (*crossbar analysis, memristors, stacked and layered design based approaches*) to stem such experimental research avenues. Table 4 and [Fig 9] provide a summarised visual of the progression from 1st to 3rd generation of neural networks, as well as core topical research focus areas of importance to inspire and drive new and novel innovations in the next generation fabric AI inspired (e-textiles).

Key findings of the study include

- Identification of key technical functional properties (computational, monitoring, measuring, communications, energy) required to be taken into consideration in a fabric based neural network workflow.
- Highlighting SNN architectural elements of relevance for consideration in e-textiles innovations such as e-textile artificial fabric neurons, fabric synapses and fabric neural networks.
- SNN architectural design inspiration from multilayered (stacked and woven) neural network design approaches.
- Consideration of SNN neuronal encoding and spike train pattern classifications that have the potential to drive research linked to fabric SNN classification templates.
- Identification of Neuromorphic computing hardware architectural design elements providing inspiration to the future design of e-textiles (crossbar array, wearable memory/memristor, 2D/3D vertical stacking architectural layout).

Continued research is required in this area. Key research questions and challenges still remain unanswered, hence validating the need for further research in this space. Such challenges and future research investigations include the following

- Advancements in the specification, design and verification of Fabric AI.
- Consideration around the identification and development of a Fabric AI based development language.
- Investigation into how AI algorithms can be embedded in an operational manner in a Fabric AI environment.
- In a textile environment what methods or processes can be applied to enable ML based data abstraction and processing.
- Specification and formalisation of textile driven properties to support fabric AI systems.
- The need to further investigate research around the verification of Fabric AI approaches, delving into trustworthy and explainable Fabric AI.

AI technologies have developed at a much quicker pace over the past few years, it's now time for the e-textiles domain to embrace such advancements and build on core defined elements and properties in order to stem new and exciting research driven innovations in the e-textiles domain.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

REFERENCES

[1] S. Jiang, O. Stange, F. O. Bcbtcke, S. Sultanova, and L. Sabantina, "Applications of smart clothing—A brief overview," *Commun. Develop. Assembling Textile Products*, vol. 2, no. 2, pp. 123–140, Nov. 2021.

[2] (Nov. 2022). *Electronic Textiles Market Size Shares by 2028 Revenue, Cost Analysis, Gross Margins, Future Investment Segmentation by Types, Applications Key Players, Market Dynamics*. [Online]. Available: https://www.globenewswire.com

[3] F. Mariani, M. Serafini, I. Gualandi, D. Arcangeli, F. Decataldo, L. Possanzini, M. Tessarolo, D. Tonelli, B. Fraboni, and E. Scavetta, "Advanced wound dressing for real-time pH monitoring," *ACS Sensors*, vol. 6, no. 6, pp. 2366–2377, Jun. 2021.

[4] K. Arquilla, A. Webb, and A. Anderson, "Textile electrocardiogram (ECG) electrodes for wearable health monitoring," *Sensors*, vol. 20, no. 4, p. 1013, Feb. 2020.

[5] A. Ivanoska-Dacikj and U. Stachewicz, "Smart textiles and wearable technologies—Opportunities offered in the fight against pandemics in relation to current COVID-19 state," *Rev. Adv. Mater. Sci.*, vol. 59, no. 1, pp. 487–505, Jan. 2020.

[6] T. Hughes-Riley, T. Dias, and C. Cork, "A historical review of the development of electronic textiles," *Fibers*, vol. 6, no. 2, p. 34, May 2018.

[7] X. Zhang and S. Xu, "Research on image processing technology of computer vision algorithm," in *Proc. Int. Conf. Comput. Vis., Image Deep Learn. (CVIDL)*, Jul. 2020, pp. 122–124.

[8] K. Rajan, E. Garofalo, and A. Chiolerio, "Wearable intrinsically soft, stretchable, flexible devices for memories and computing," *Sensors*, vol. 18, no. 2, p. 367, Jan. 2018.

[9] A. Jo, Y. Seo, M. Ko, C. Kim, H. Kim, S. Nam, H. Choi, C. S. Hwang, and M. J. Lee, "Textile resistance switching memory for fabric electronics," *Adv. Funct. Mater.*, vol. 27, no. 15, Apr. 2017, Art. no. 1605593.

[10] J.-W. Han and M. Meyyappan, "Copper oxide resistive switching memory for e-textile," *AIP Adv.*, vol. 1, no. 3, Sep. 2011, Art. no. 032162.

[11] N. Yuldoshev, B. Tursunov, and S. Qozoqov, "Use of artificial intelligence methods in operational planning of textile production," *J. Process Management. New Technol.*, vol. 6, no. 2, pp. 41–51, 2018.

[12] C. Li, J. Li, Y. Li, L. He, X. Fu, and J. Chen, "Fabric defect detection in textile manufacturing: A survey of the state of the art," *Secur. Commun. Netw.*, vol. 2021, pp. 1–13, May 2021.

[13] P. Y. Taser and V. Akram, "Machine learning techniques for IoT-based indoor tracking and localization," in *Emerging Trends in IoT and Integration With Data Science, Cloud Computing, and Big Data Analytics*. PA, USA: IGI Global, 2022, pp. 123–145. [Online]. Available: https://www.igi-global.com/gateway/chapter/290078

[14] S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, "MyWear: A novel smart garment for automatic continuous vital monitoring," *IEEE Trans. Consum. Electron.*, vol. 67, no. 3, pp. 214–222, Aug. 2021.

[15] C. Elo, E.-L. Rauhala, T. Ihalainen, O. C. Buruk, T. Vihri, E. SipilCB, T. Kosonen, and J. Virkki, "E-textiles assisting healthcare, rehabilitation, and well-being—To whom, for what, and how?" in *Proc. IEEE 10th Int. Conf. Serious Games Appl. Health (SeGAH)*, Oct. 2022, pp. 1–8.

[16] T. Fernández-Caramés and P. Fraga-Lamas, "Towards the Internet-of-Smart-Clothing: A review on IoT wearables and garments for creating intelligent connected E-textiles," *Electronics*, vol. 7, no. 12, p. 405, Dec. 2018.

[17] J. Shi, S. Liu, L. Zhang, B. Yang, L. Shu, Y. Yang, M. Ren, Y. Wang, J. Chen, W. Chen, Y. Chai, and X. Tao, "Smart textile-integrated microelectronic systems for wearable applications," *Adv. Mater.*, vol. 32, no. 5, Feb. 2020, Art. no. 1901958.

[18] D. P. Banumathi, T. S. Sree, and S. Priya, "Artificial intelligence techniques in textile fabric inspection," *Int. J. Comput. Sci. Netw.*, vol. 4, no. 5, pp. 2277–5420, Oct. 2015.

[19] C.-F.-J. Kuo and C.-J. Lee, "A back-propagation neural network for recognizing fabric defects," *Textile Res. J.*, vol. 73, no. 2, pp. 147–151, Feb. 2003.

[20] M. P. Sikka, A. Sarkar, and S. Garg, "Artificial intelligence (AI) in textile industry operational modernization," *Res. J. Textile Apparel*, vol. 2022, pp. 1–10, Apr. 2022.

[21] F. Jia, S. Yin, L. Chen, and X. Chen, "The circular economy in the textile and apparel industry: A systematic literature review," *J. Cleaner Prod.*, vol. 259, Jun. 2020, Art. no. 120728.

[22] Y. Hong, X. Zeng, P. Brunixaux, and Y. Chen, "Evaluation of fashion design using artificial intelligence tools," in *Artificial Intelligence for Fashion Industry in the Big Data Era*. New York, NY, USA: Springer, 2018. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-13-0080-6_12

[23] X. Ren, S. Niu, and X. Huang, "Research on 3D simulation design and dynamic virtual display of clothing flexible body," Res. Square, Tech. Rep., Feb. 2023.

[24] G. Andreoni, C. Standoli, and P. Perego, "Defining requirements and related methods for designing sensorized garments," *Sensors*, vol. 16, no. 6, p. 769, May 2016.

[25] J. Chan and S. Gollakota, "Data storage and interaction using magnetized fabric," in *Proc. 30th Annu. ACM Symp. User Interface Softw. Technol.*, Oct. 2017, pp. 655–663.

[26] G. Loke, T. Khudiyev, B. Wang, S. Fu, S. Payra, Y. Shaoul, J. Fung, I. Chatziveroglou, P.-W. Chou, I. Chinn, W. Yan, A. Gitelson-Kahn, J. Joannopoulos, and Y. Fink, "Digital electronics in fibres enable fabric-based machine-learning inference," *Nature Commun.*, vol. 12, no. 1, p. 3317, Jun. 2021.

[27] G. Loke, W. Yan, T. Khudiyev, G. Noel, and Y. Fink, "Recent progress and perspectives of thermally drawn multimaterial fiber electronics," *Adv. Mater.*, vol. 32, no. 1, Jan. 2020, Art. no. 1904911.

[28] S. Park, G. Loke, Y. Fink, and P. Anikeeva, "Flexible fiber-based optoelectronics for neural interfaces," *Chem. Soc. Rev.*, vol. 48, no. 6, pp. 1826–1852, 2019.

[29] W. Zeng, L. Shu, Q. Li, S. Chen, F. Wang, and X.-M. Tao, "Fiber-based wearable electronics: A review of materials, fabrication, devices, and applications," *Adv. Mater.*, vol. 26, no. 31, pp. 5310–5336, Aug. 2014.

[30] C. Lee, J. Tan, N. Y. K. Lam, H. T. Tang, and H. H. Chan, "The effectiveness of e-textiles in providing thermal comfort: A systematic review and meta-analysis," *Textile Res. J.*, vol. 93, no. 7, 2022, Art. no. 00405175221124975.

[31] J. Coulter, J. Magee, and C. Nugent, "E-textiles: A soft touch barometer for female students to self-manage their stress," *J. Textile Des. Res. Pract.*, vol. 10, no. 3, pp. 243–273, Sep. 2022.

[32] A. Rajappan, B. Jumet, R. A. Shveda, C. J. Decker, Z. Liu, T. F. Yap, V. Sanchez, and D. J. Preston, "Logic-enabled textiles," *Proc. Nat. Acad. Sci. USA*, vol. 119, no. 35, Aug. 2022, Art. no. e2202118119.

[33] F. Cleary, D. C. Henshall, and S. Balasubramaniam, "On-body edge computing through E-textile programmable logic array," *Frontiers Commun. Netw.*, vol. 2, p. 18, Jun. 2021.

[34] A. Taherkhani, A. Belatreche, Y. Li, G. Cosma, L. P. Maguire, and T. M. McGinnity, "A review of learning in biologically plausible spiking neural networks," *Neural Netw.*, vol. 122, pp. 253–272, Feb. 2020.

[35] A. Ooyen, "Methods in neuronal modeling," *Int. J. Neural Syst.*, vol. 10, pp. 331–332, Jan. 2000.

[36] E. M. Izhikevich, "Simple model of spiking neurons," *IEEE Trans. Neural Netw.*, vol. 14, no. 6, pp. 1569–1572, Nov. 2003.

[37] S. Qiang, T. Carey, A. Arbab, W. Song, C. Wang, and F. Torrisi, "Wearable solid-state capacitors based on two-dimensional material all-textile heterostructures," *Nanoscale*, vol. 11, no. 20, pp. 9912–9919, 2019.

[38] T. Blecha and D. Moravcova, "Methods for the capacity increasing of textile capacitors," in *Proc. 45th Int. Spring Seminar Electron. Technol.*, 2022, pp. 1–5.

[39] A. Bonfiglio, D. de rossi, T. Kirstein, I. Locher, F. Mameli, R. Paradiso, and G. Vozzi, "Organic field effect transistors for textile applications," *IEEE Trans. Inf. Technol. Biomed.*, vol. 9, no. 3, pp. 319–324, Sep. 2005.

[40] T. Carey, S. Cacovich, G. Divitini, J. Ren, A. Mansouri, J. M. Kim, C. Wang, C. Ducati, R. Sordan, and F. Torrisi, "Fully inkjet-printed two-dimensional material field-effect heterojunctions for wearable and textile electronics," *Nature Commun.*, vol. 8, no. 1, pp. 1–5, Oct. 2017.

[41] F. Cleary, W. Srisa-an, B. Gil, J. Kesavan, T. Engel, D. C. Henshall, and S. Balasubramaniam, "Wearable fabric μ brain enabling on-garment edge-based sensor data processing," *IEEE Sensors J.*, vol. 22, no. 21, pp. 20839–20854, Nov. 2022.

[42] D. Beeman, *Hodgkin-Huxley Model*. New York, NY, USA: Springer, 2013, pp. 1–13.

[43] N. Lindrupsen, "Exploring textile controllers for computer music," M.S. thesis, Univ. Oslo, Institutt for Informatikk, Oslo, Norway, 2021.

[44] Y. Park, M.-J. Park, and J.-S. Lee, "Reduced graphene oxide-based artificial synapse yarns for wearable textile device applications," *Adv. Funct. Mater.*, vol. 28, no. 42, Oct. 2018, Art. no. 1804123.

[45] S. Ham, M. Kang, S. Jang, J. Jang, S. Choi, T.-W. Kim, and G. Wang, "One-dimensional organic artificial multi-synapses enabling electronic textile neural network for wearable neuromorphic applications," *Sci. Adv.*, vol. 6, no. 28, Jul. 2020, Art. no. eaba1178.

[46] X. She, "Design and optimization of heterogeneous feedforward spiking neural network for spatiotemporal data processing," Ph.D. dissertation, Georgia Inst. Technol., Atlanta, GA, USA, 2022.

[47] J. Shen, J. K. Liu, and Y. Wang, "Dynamic spatiotemporal pattern recognition with recurrent spiking neural network," *Neural Comput.*, vol. 33, no. 11, pp. 2971–2995, 2021.

[48] P. Stoliar, O. Schneegans, and M. J. Rozenberg, "Implementation of a minimal recurrent spiking neural network in a solid-state device," *Phys. Rev. Appl.*, vol. 16, no. 3, Sep. 2021, Art. no. 034030.

[49] M. Pfeiffer and T. Pfeil, "Deep learning with spiking neurons: Opportunities and challenges," *Frontiers Neurosci.*, vol. 12, p. 774, Oct. 2018.

[50] D. Auge, J. Hille, E. Mueller, and A. Knoll, "A survey of encoding techniques for signal processing in spiking neural networks," *Neural Process. Lett.*, vol. 53, no. 6, pp. 4693–4710, Dec. 2021.

[51] F. Zeldenrust, W. J. Wadman, and B. Englitz, "Neural coding with bursts—Current state and future perspectives," *Frontiers Comput. Neurosci.*, vol. 12, p. 48, Jul. 2018.

[52] I.-M. Comşa, L. Versari, T. Fischbacher, and J. Alakuijala, "Spiking autoencoders with temporal coding," *Frontiers Neurosci.*, vol. 15, Aug. 2021, Art. no. 712667.

[53] W. Guo, M. E. Fouda, A. M. Eltawil, and K. N. Salama, "Neural coding in spiking neural networks: A comparative study for robust neuromorphic systems," *Frontiers Neurosci.*, vol. 15, pp. 1–12, Mar. 2021.

[54] M. Sorbaro, Q. Liu, M. Bortone, and S. Sheik, "Optimizing the energy consumption of spiking neural networks for neuromorphic applications," *Frontiers Neurosci.*, vol. 14, p. 662, Jun. 2020.

[55] Y. Shi, L. Nguyen, S. Oh, X. Liu, and D. Kuzum, "A soft-pruning method applied during training of spiking neural networks for in-memory computing applications," *Frontiers Neurosci.*, vol. 13, p. 405, Apr. 2019.

[56] N. Rathi, P. Panda, and K. Roy, "STDP-based pruning of connections and weight quantization in spiking neural networks for energy-efficient recognition," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, vol. 38, no. 4, pp. 668–677, Apr. 2019.

[57] M. Davies, N. Srinivasa, T.-H. Lin, G. Chinya, Y. Cao, S. H. Choday, and G. Dimou, "Loihi: A neuromorphic manycore processor with on-chip learning," *IEEE Micro*, vol. 38, no. 1, pp. 82–99, Jan. 2018.

[58] A. Lines, P. Joshi, R. Liu, S. McCoy, J. Tse, Y. Weng, and M. Davies, "Loihi asynchronous neuromorphic research chip," in *Proc. 24th IEEE Int. Symp. Asynchronous Circuits Syst. (ASYNC)*, May 2018, pp. 32–33.

[59] H. Cheng, W. Wen, C. Wu, S. Li, H. H. Li, and Y. Chen, "Understanding the design of IBM neurosynaptic system and its tradeoffs: A user perspective," in *Proc. Design, Autom. Test Eur. Conf. Exhib.*, Mar. 2017, pp. 139–144.

[60] Q. Xia and J. J. Yang, "Memristive crossbar arrays for brain-inspired computing," *Nature Mater.*, vol. 18, no. 4, pp. 309–323, Apr. 2019.

[61] H. Kim, M. R. Mahmoodi, H. Nili, and D. B. Strukov, "4K-memristor analog-grade passive crossbar circuit," *Nature Commun.*, vol. 12, no. 1, p. 5198, Aug. 2021.

[62] Y. Zhang, Z. Wang, J. Zhu, Y. Yang, M. Rao, W. Song, Y. Zhuo, X. Zhang, M. Cui, L. Shen, R. Huang, and J. Joshua Yang, "Brain-inspired computing with memristors: Challenges in devices, circuits, and systems," *Appl. Phys. Rev.*, vol. 7, no. 1, Mar. 2020, Art. no. 011308.

[63] H. Kim, M.-J. Choi, J. M. Suh, J. S. Han, S. G. Kim, Q. V. Le, S. Y. Kim, and H. W. Jang, "Quasi-2D halide perovskites for resistive switching devices with ON/OFF ratios above 109," *NPG Asia Mater.*, vol. 12, no. 1, p. 21, Dec. 2020.

[64] W. Xu, J. Wang, and X. Yan, "Advances in memristor-based neural networks," *Frontiers Nanotechnol.*, vol. 3, Mar. 2021, Art. no. 645995.
[65] Y. Liu, X. Zhou, H. Yan, Z. Zhu, X. Shi, Y. Peng, L. Chen, P. Chen, and H. Peng, "Robust memristive fiber for woven textile memristor," *Adv. Funct. Mater.*, vol. 32, no. 28, Jul. 2022, Art. no. 2201510.
[66] J. Stanley, J. A. Hunt, P. Kunovski, and Y. Wei, "A review of connectors and joining technologies for electronic textiles," *Eng. Rep.*, vol. 4, no. 6, Jun. 2022, Art. no. e12491.

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