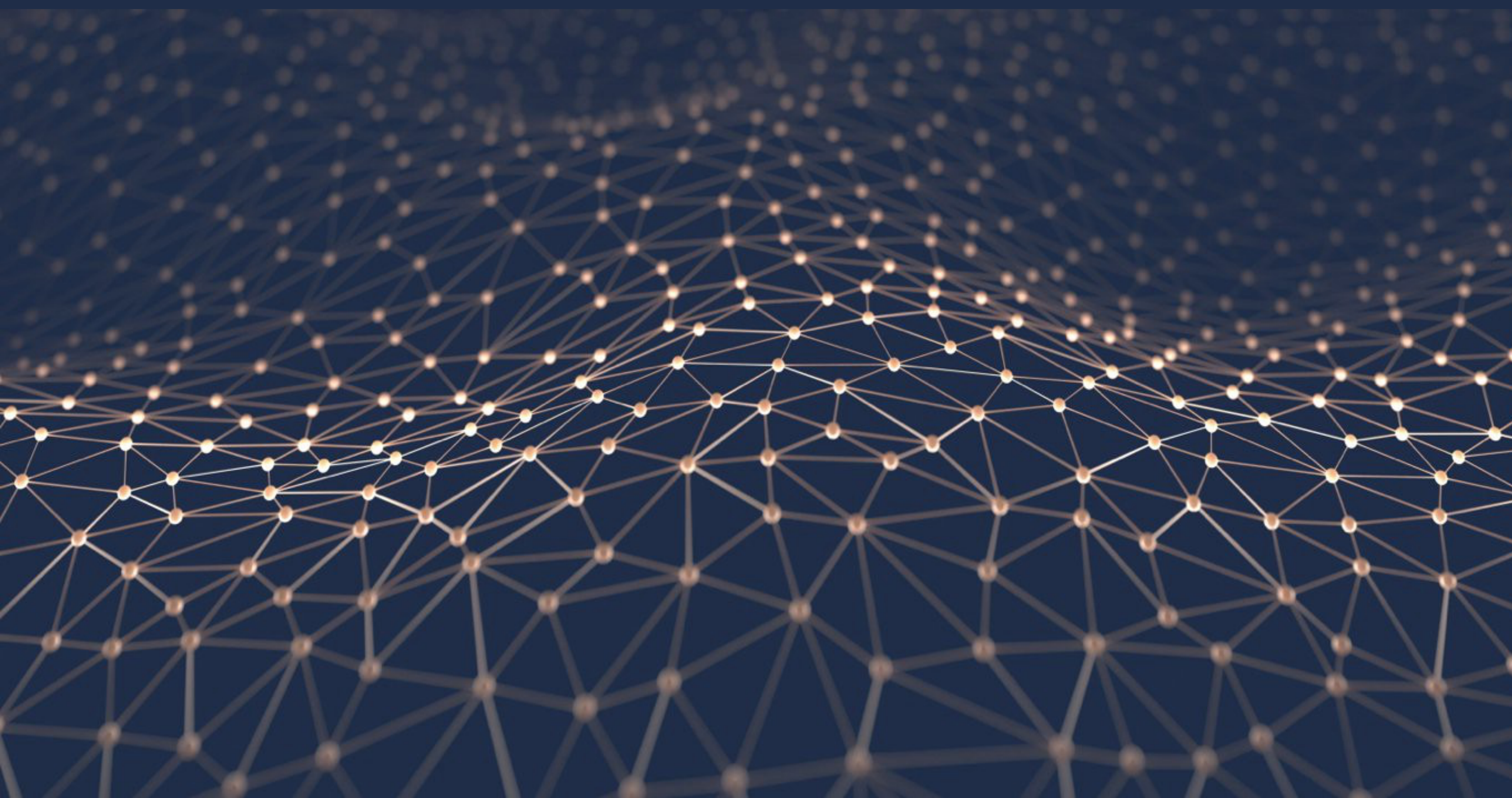
Deliverable D4.2:

Report on different application classification tasks: where k-NET can be a game changer



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2. Project abstract:

Artificial neural networks represent a key component of neuro-inspired computing for non-Boolean computational tasks. They emulate the brain by using nonlinear elements acting as neurons that are interconnected through artificial synapses. However, such physical implementations face two major challenges. First, interconnectivity is often constrained because of limits in lithography techniques and circuit architecture design; connections are limited to 100s, compared with 10000s in the human brain. Second, changing the weight of these individual interconnects dynamically requires additional memory elements attached to these links.

Here, we propose an innovative architecture to circumvent these issues. It is based on the idea that dynamical hyperconnectivity can be implemented not in real space but in reciprocal or k-space. To demonstrate this novel approach, we have selected ferromagnetic nanostructures in which populations of spin waves – the elementary excitations – play the role of neurons. The key feature of magnetization dynamics is its strong nonlinearity, which, when coupled with external stimuli like applied fields and currents, translates into two useful features: (i) nonlinear interactions through exchange and dipole dipole interactions couple potentially all spin wave modes together, thereby creating high connectivity; (ii) the strength of the coupling depends on the population of each k mode, thereby allowing for synaptic weights to be modified dynamically. The breakthrough concept here is that real-space interconnections are not necessary to achieve hyper-connectivity or reconfigurable synaptic weights.

The final goal is to provide a proof-of-concept of a k-space neural network based on interacting spin waves in low-loss materials such as yttrium iron garnet (YIG). The relevant spin wave eigenmodes are in the GHz range and can be accessed by microwave fields and spin-orbit torques to achieve k-space Neural computation with magnEtic excitations.

3. Context and Summary

The role of deliverable D4.2 is to identify the different application tasks where k-NET can be a game changer and to draw perspectives to investigate them. It also addresses part of the evaluation committee interrogations that has been raised about the content of D4.1 at the first review meeting which were written as:

"*The report D4.1 should be amended to include: 1) A basic NN market survey, describing available technology and the challenges it faces 2)Areas that would need to be addressed in order to commercialize a successful k-NET implementation (specifications that need to be met, integration within existing technology) 3)Possible commercial applications for k-NET (beyond the prototype) 4)Clear benchmarking criteria for the k-NET prototype, based on point 3). These can be done by adding supplementary sections or by reshuffling existing sections. This should be implemented, and the report resubmitted by month 19 (30 Jun 2022, same time as D4.2)"*

Deliverable 4.2 should be read as a separate but logically articulated continuation of Deliverable 4.1. In D4.1, we draw an overview of the alternative technologies to the k-NET approach, i.e., the physical implementations of neuromorphic approaches. D4.1 thus provided an analysis of the technologically relevant paths with strong economic potential. Within the context of k-NET and 2 years after submission we could conclude on the relevance of the approaches that we proposed. More specifically, an important point relevant to k-NET is that neuromorphic devices based on magnetization dynamics have been doing significant progress and they are among the few contenders for large scale integration. Even so, the specific approach proposed in k-NET remains unique in all its aspects as it was at the date of submission. To conclude, in D4.1 we stated that the next step would be to provide a clear focus on the pathway that will provide the ground for k-NET economical potential. Here, D4.2 explores how the different methodologies that are recognized to be relevant for neuromorphic technologies can be implemented using k-NET concepts. In D4.2, we describe how to make focus on a classical use case “spoken vowel recognition” that can be implemented within the time frame of k-NET as an exemplary proof-of-concept demonstration. Correspondingly, please note, that the generality of k-NET’s approach also can allow to perform other typical classification tasks in neuromorphic computing such as “handwritten digits recognition” as well. The future k-NET chips could thus be used for different task in neuromorphic computing, which also enforces k-NETs potential for the neuromorphic computing market in the next decade (cf. section on the market analysis).

In this context, D4.2 furthermore extrapolates the economic impact of k-NET approaches and compares it to the extrapolated impacts of competing approaches. It sets the scene for the environment in which k-NET will evolve, focusing not only on the hardware part but also on applications and software trends. In particular, this section mentions the main market players and drivers, the threats and opportunities for k-NET.

In the light of the Deliverable 4.1 and 4.2, it is shown that several technologically and commercially credible development schemes exist. In the short and medium term, the chosen approach of focusing on spoken vowel recognition is very relevant for two reasons: there are direct commercial applications for this use-case with significant potential and it is a use-case that can be easily extrapolated for future longer-term research if successful.

- **Purpose of the document:**

The document has one main objective which is to provide tangible and up-to-date elements that allow the initiation of the technology development phase in alignment with the wider operational objectives of the project. Namely, to enable a TRL increase, but also to match the market needs and find a positioning that can lead to commercialisation.

It is indeed crucial to define an ambitious but realistic path with a vision that fits with the consortium's ability to achieve within the timeframe of the project a first step towards the development of a ready for the market magnonic neuromorphic technology.

In addition to guiding the choice of the proof of concept and selecting, for example, the elements to be compared as a priority (and therefore on which it is important to concentrate efforts), this document is a pivot of the exploitation strategy. The more detailed knowledge of the competitive environment and market players provides a complete vision of the potential stakeholders and how to address them. In a very practical way, it can be used, for example, to find out who to contact, which partnerships to consider or to prepare the end-user’s workshop.

This document is therefore primarily intended for the members of the consortium. It provides a shared vision and factual arguments for arbitrating the various choices to be made during the project.

But it also allows these same elements to be shared with the other actors involved in the project. On the one hand, the Commission and the reviewers (in particular the innovation radar expert), and on the other hand the members of the Exploitation Committee. Thanks to this document, the latter can have more information, but they can also better understand the elements on which the consortium bases its choice of development and exploitation strategy. They will therefore be able to provide more relevant and appropriate feedback to initiate a collaborative and iterative approach.

Indeed, if this document is a real keystone, it remains only a first step in the exploitation strategy. It can and must continue to evolve according to the comments made by the experts, the changes in the context in which the project is evolving or the successes and failures of the development of the technology.

These evolutions can in particular be considered in the next communication, dissemination and exploitation plans.

4. Magnetic materials based neuromorphic proof of concepts

4.1 Theoretical proposal

Over the past few years, a number of theoretical proposals have been put forward to use magnetic materials and spintronics for neuromorphic computing. Many of these are based on the concept of physical reservoir computing, which seeks to harness the nonlinearity and recurrence inherent to dynamical systems as a physical resource for computation. In general terms, the reservoir computing approach offers a straightforward way to use recurrent neural networks by performing training only on the outputs of the network. A number of proposals are based on arrays of coupled spintronic devices, such as spin-torque nano-oscillators (STNOs) [1], [2], superparamagnetic magnetic tunnel junctions (MTJs) [3], and artificial spin ice [4]. These represent a natural spatial implementation of a recurrent neural network, where each device or node plays the role of a neuron. However, coupling between nodes typically occurs through dipolar interactions, which represent an all-to-all coupling and are set by the geometrical layout of the device array. For the STNO arrays, standard reservoir computing benchmarks such as short-term memory (STM) and parity check (PC) have been performed [1], along with tasks such as handwritten digit recognition and nonlinear time series prediction [2]. For the implementation involving superparamagnetic MTJs, it is proposed that voltage-control of the magnetic anisotropy can offer an additional handle to set the state of the elements. Here, a nonlinear time series prediction task (NARMA10) has also been demonstrated [3]. STM and PC tasks have also been demonstrated for artificial spin ice systems, which exhibit geometrical frustration in addition to dipolar coupling between elements [4]. Instead of using interconnected devices, other proposed schemes use nonuniform magnetic textures as the physical "substrate" for reservoir computing. One example relies on random skyrmion textures [5], whereby electrical currents flow through the textures to provide a nonlinear response to inputs, which occurs through a combination of spin torques and anisotropic magnetoresistance (as the readout). The performance of the reservoir is tested using a pattern recognition task based on sequences of sine and square waveforms, where both spatial and temporal multiplexing of the outputs are studied. This idea has recently been extended to simpler stripe domain structures, where it has been shown that 4-pixel pattern recognition tasks can be performed [6]. Another involves spin waves propagating through a stripe domain structure [7], which provide a nonlinear transformation of the input spin wave spectrum. It is shown that such a system can be used to perform temporal XOR tasks.

A number of other proposals also rely on spin waves for computation, as is the case in the k-NET project. One of the earlier proposals focused YIG films with different input and output contacts [8], [9]. Wave interference patterns generated by several input excitation sources, which are subsequently detected using different detector arrangements, can be used with machine learning to reconstruct input signals. Another approach (by one member of k-NET consortium) more closely resembles a feedforward neural network, which involves propagating spin waves through a uniformly-magnetised medium over which an array of nanomagnets is present [10]. Each nanomagnet generates a stray dipolar field on the magnetic film, and training is used to induce particular interference patterns to match a desired output. It is shown that this system can perform frequency separation and vowel recognition.

Other studies have also appeared where the focus is on the performance of single devices. In one example, the transition between chaotic and nonchaotic dynamics is explored as a resource for reservoir computing [11] where it is shown that nonlinear time series prediction (NARMA2) can be performed. A similar analysis is performed for a voltage-controlled MTJ, where the transient dynamics within a macrospin approximation is used to perform similar nonlinear time series prediction [12]. Finally, the spiking dynamics of spin-Hall nano-oscillators (SHNOs) have also been investigated through simulation for neuromorphic computing [13] . This work represents a more traditional approach in which conditions under which spiking neurons can be combined together for basic neural network behaviour are investigated. Such oscillators are shown to be interesting building blocks for such architectures.

4.2 Experimental implementations:

While theoretical proposals on neuromorphic computing with magnetic and spintronic devices are numerous, the same cannot be said for actual experimental implementations of which only a handful has been reported in the literature to date. The first clear demonstration employed a single magnetic vortex nano-oscillator, based on a magnetic tunnel junction, where the amplitude dynamics of the oscillator signal is used as a physical resource for reservoir computing [14]. The amplitude dynamics was chosen as it is more robust to noise compared with phase dynamics. It was shown that the nano-oscillator can result in spoken-digit recognition rates exceeding 80% with spectrogram filtering and 95% with cochlear filtering.

By using an array of such vortex nano-oscillators, coupled together through dipolar interactions, it has been shown that tasks such as vowel recognition can also be performed [15]. Instead of using a pure reservoir computing approach, where training is only performed on the outputs, here the synchronization patterns of the coupled oscillators are tuned to provide sufficient separation in order to perform the vowel recognition tasks. It therefore represents an approach closer to training a neural network, albeit a simplistic one with only four coupled oscillators. Nevertheless, recognition rates exceeding 80% can be achieved.

Another successful experimental implementation relies on the time delay architecture for reservoir computing, where an active delay line with feedback is used to reconstruct a network of virtual nodes in the time domain, rather than in space. The implementation consists of an active ring oscillator based on propagating spin waves in a yttrium iron garnet system, where the delayed feedback dynamics are used to provide fading memory and recurrence [16]. As in the theoretical studies discussed above, it is shown that this system performs well in standard benchmarks such as STM and PC.

Finally, artificial spin ice has also been shown to be an effective reservoir. In this work, the size of the nanoelements comprising the ice structure is chosen such that the macrospin and vortex ground states are both metastable states. Each of these states couple differently to one another, with Ising-like behaviour exhibited by the macrospin states, while vortices minimize stray dipolar fields that results in weaker coupling. This results in nontrivial phenomena such as ratchet-like vortex injection and history-dependent nonlinear fading memory, features that are harnessed for computation. Interestingly, the macrospin and vortex states possess distinct microwave responses to excitation fields, which allows a spin wave “fingerprinting” to be used as an effective readout mechanism. It is shown that such a system can be used for nonlinear time series prediction.

5. Overview about k-NET from a technological perspective

5.1 General overview on k-NETs operating principle

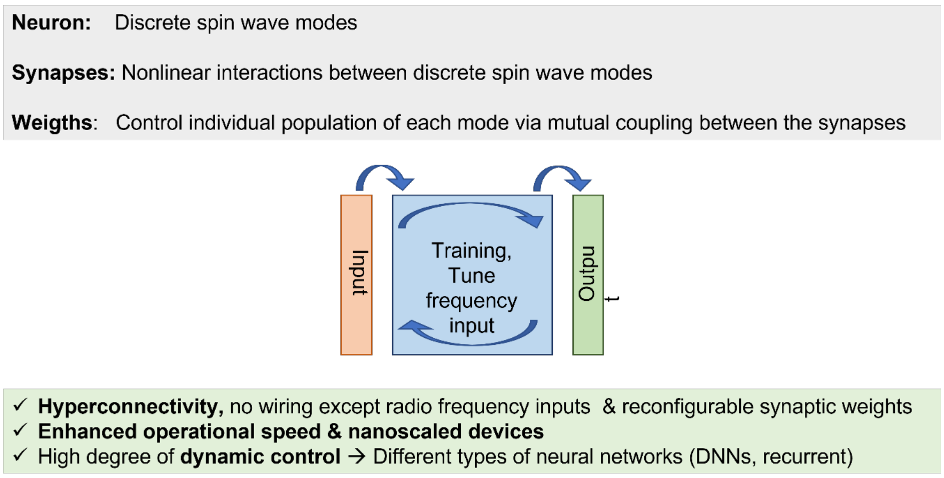


Figure 1: k-NET advantages and type of envisioned operation in a nutshell

As can be also found in more detail in the first project review report and specific deliverables the typical k-NET system looks like schematically shown **in Figure 1 for the most generic concept and more concretely displayed in Figure 2**. The k-NET technology uses simple devices based on a single small microstructure in the micrometer range made of LPE grown Yttrium Iron Garnet (YIG). In these confined geometries the spin wave (SW) modes are quantized and form a discrete set of modes with different wavevectors labeled with the mode-index k. In k-NET, these discrete spin wave modes serve as the neurons. This is also schematically shown for a set of selected modes in **Figure 2**.

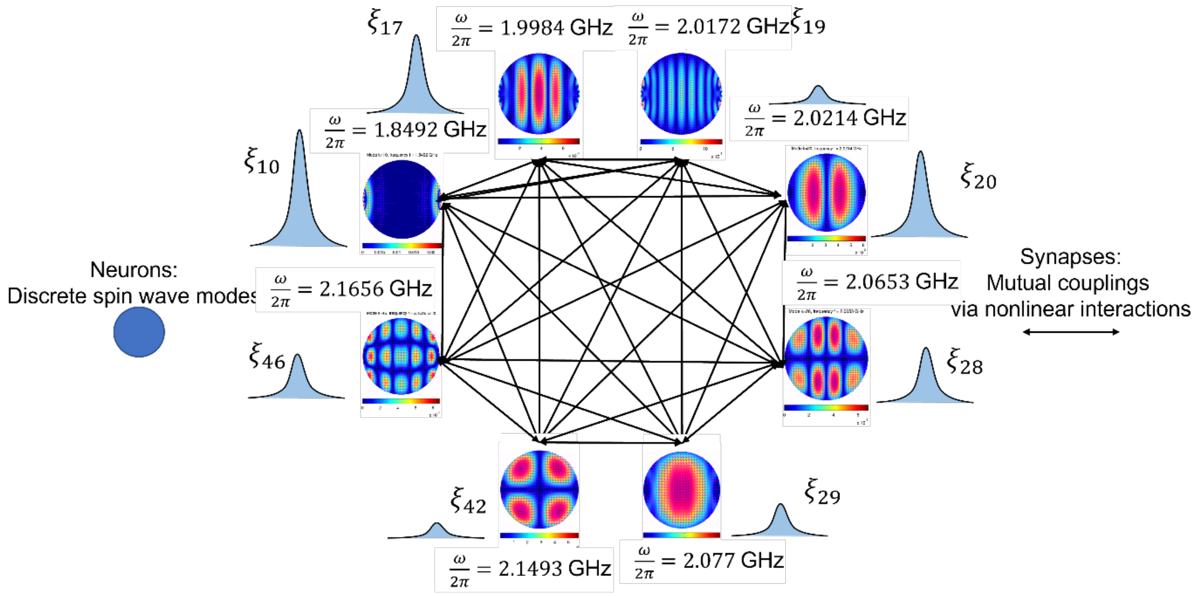


Figure 2: *Illustration of the k-NET neuromorphic network in k-space for eight selected modes for better visibility. The synaptic weight of each mode in this ensemble is characterized by the individual spin wave amplitude (occupation number where the underscore indicated the mode number found in experiments and simulations. The amplitude distribution is only a schematic example to illustrate the principle and not deduced from a specific measurement here.)*

In the linear regime, these modes are independent from each other and do not interact. However, to realize a neuromorphic network (NN), synapses that is the couplings between theses discrete sets of modes need are required. Furthermore, the synaptic weight needs to be controlled, to control the channeling of information as the basic ingredient to program a neural network.

This is possible by operating in the nonlinear regime, where the spin wave modes are mutually coupled and hence undergo nonlinear interactions. The synaptic weight can be changed by altering the populations per spin wave mode. Most of the modes in k-space are short wavelength modes which cannot be excited by common inductive techniques. Instead, the magnon modes are excited by means of parametric pumping. In the nonlinear regime, the short-wavelength modes are coupled to the uniform precession modes of ferromagnetic resonance (k=0). That uniform mode is excited by the ac magnetic field generated by induction from radio frequency antennae either on top of or in close vicinity to the YIG microstructure with a frequency ω_P. In the nonlinear regime, SW instabilities occur if the pumping amplitude exceeds a specific threshold value. At this threshold, the energy pumped into these discrete spin wave modes (at $\omega_{\pm k_i} = \omega_P/2$) compensates the spin wave losses of these modes and the individual spin wave's mode population grows exponentially. A change in the pumping frequencies has also an impact on the individual population of each mode in the discrete SW mode spectrum in k-space as we are also going to discuss in the proposed methods to realize the first k-NET proof-of-concept device.

5.2 First results for the k-NET proof of concept device

Referring to the realization of the excitation of our spin wave mode set, in the first generation of the k-NET sample, the choice of the antennae shape should also enable to either control the in-plane or the out-of-plane dynamic component of the time dependent magnetic field. Thus, different shapes of antennae were employed in the first generation of a k-NET sample as well as differently sized YIG micro disks to narrow on the optimal design of a first proof-of-concept device.

Note, that three different types of measurement techniques were utilized to characterize the first generation of the k-NET devices (see **Figure 3**). These techniques are vector-network analysis ferromagnetic resonance (VNA-FMR), micro-focused Brillouin- light scattering (μ-BLS) and magnetic resonance force microscopy (MRFM), which is employed by different partners of the consortium.

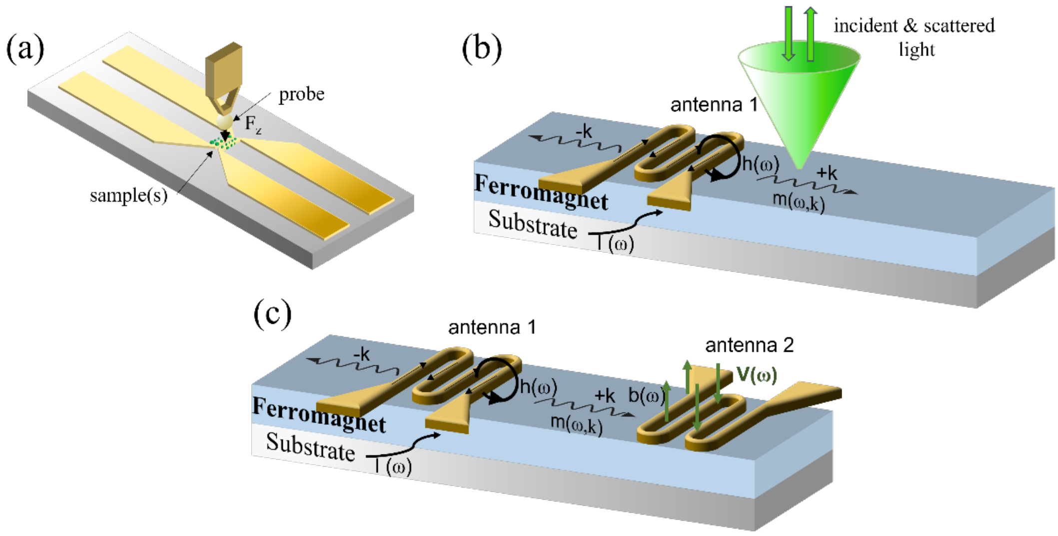


Figure 3: *Schematics of the employed measurement techniques (a) Magnetic resonance force microscopy (MRFM) (b) Micro focused Brillouin light scattering (BLS) (c) Electrical detection: Propagative spin wave spectroscopy*

Peculiar requirements for each experimental approach require each slight modifications of the basic k-NET sample design, which is reflected in the different layouts,

The agreement between simulations of the magnon modes in the YIG disks and the experimental observation at the predicted frequencies is excellent (see **Figure 4**). This shows the ability of the consortium to reliably predict not only the system ground state but also most of its non-linear dynamics, enabling the future possibility to emulate device operations. The magnon modes in the YIG disks are parametrically pumped with a frequency $2f_{1,}$ for instance. The system operates then in the nonlinear regime either in with shallow nonlinearity or in a deep nonlinear regime where mode coupling dominates. In this regime, we experimentally observed the appearance of new resonance peaks depending on the frequency and power which characteristic of an energy flow from the excited modes to other modes within the same YIG disk. In terms of a neuromorphic network, such as the perceptron, the individual spin wave amplitudes depend on the frequency of the parametric drive. Thus, this dependence gives the central ability to change the synaptic weights- here in form of the specific spin wave amplitudes. In turn, speaking in terms of a neuromorphic network we are able to perform the training for the desired classification tasks with k-NET.

In principle, using the simulations, we can precisely identify the interacting modes seen in the experiments and the strength of the mode coupling, enabling to identify approaches to address them selectively. However, although it is theoretically possible, it is not practical to attempt to address a large number of individual modes within the magnon manifold at this stage. Preliminary measurements with two parametric drives at different frequencies show that the amplitude can be varied of each resonance, but the variation is currently addressed on all excited modes in the ensemble.

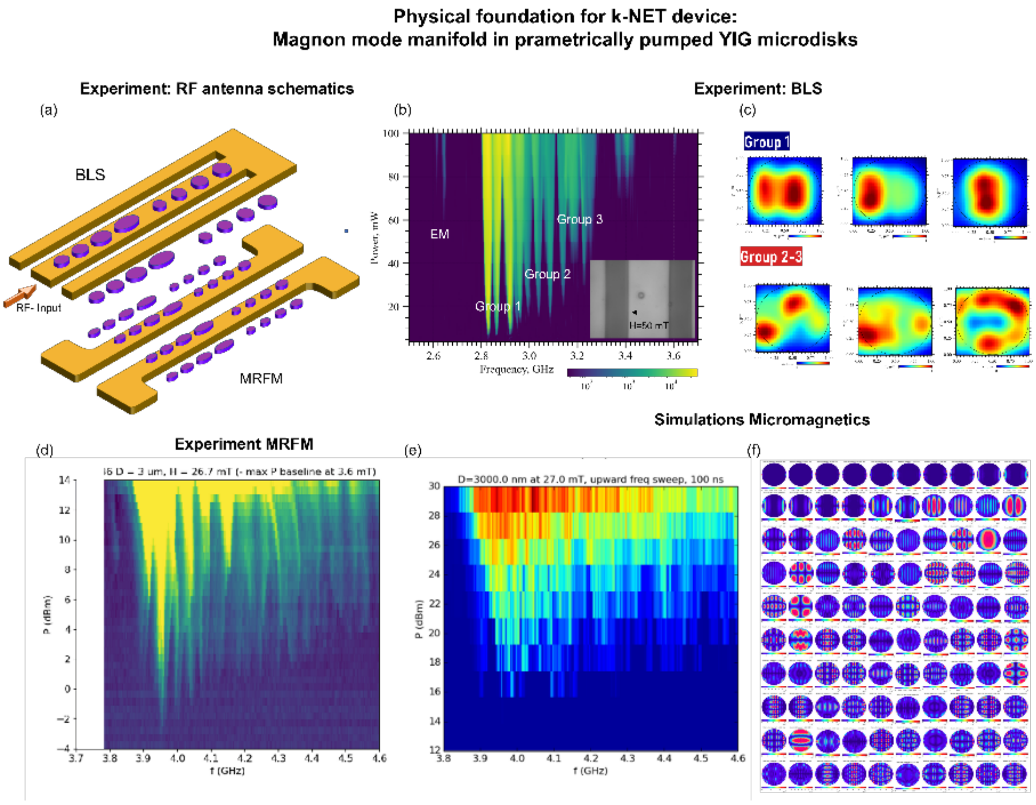


Figure 4: Results from the first generation of a k-NET using parametric pumping. We show the different antennae schematics (a) used or the different experimental setups and measurements techniques. Result from BLS measurements ((b)-(c)), MRFM measurements with one parametric frequency input ((d)-(e)) and micromagnetic simulations (f).

Thus, for a first k-NET proof-of-concept device, we will rather address the simultaneously excited modes at different frequencies all together. Specifically, we will address the entire relative amplitude distribution (magnon mode populations) within in one ensemble (see also the following paragraph and **Figures 5-6**). This is also eases the implementation of a future k-NET device as it again requires much less interconnections and decreases the device's complexity.

5.3 Proposed implementation of k-NET concept for neuromorphic computing

To date, two different feasible approaches can be envisaged to change that amplitude distribution which is **A. an "All parametric, nonlinear interacting" or B. "Parametric but with linear control knobs".** They will be explained in more detail in the following paragraph. Notably, they have both in common that as said above we treat one ensemble of parametrically excited, nonlinearly interacting spin wave modes as a set. The application of approach specific control knobs allows then to change the distribution of the synaptic weights, i.e., the individual spin wave amplitudes within this ensemble. In turn such change of the synaptic weight enables the training of our k-NET neural network. Note, that although we treat all the excited spin wave modes as a set, the dynamic control of the synaptic weight results in a "recurrent" neural network. This is in stark contrast to other emerging approaches for neuromorphic computing with spin waves in k-space, which are all based on reservoir computing.

A. "**All-parametric "**

In this all-parametric approach, we excite our magnon modes in the YIG disk into the nonlinear regime by performing simultaneous parametric pumping at different frequencies (see **Figure 5**). Ultimately, one will obtain a third subset- corresponding to the amplitude distribution of the modes. This is precisely the principle of a perceptron and more general a neural network. If then we input two (eventually N) different parametric sets of frequencies with different amplitude distribution, the two

(N) sets will excite specific sets of magnons modes that will interact nonlinearly with each other and result in another, new distribution. This principle is also schematically depicted in **Figure 5**. A single input of the k-NET device, is therefore a power spectrum S_i. In the present all-parametric scheme of excitation, the frequencies component ($2f_i$) are to address magnons modes at half their frequency.

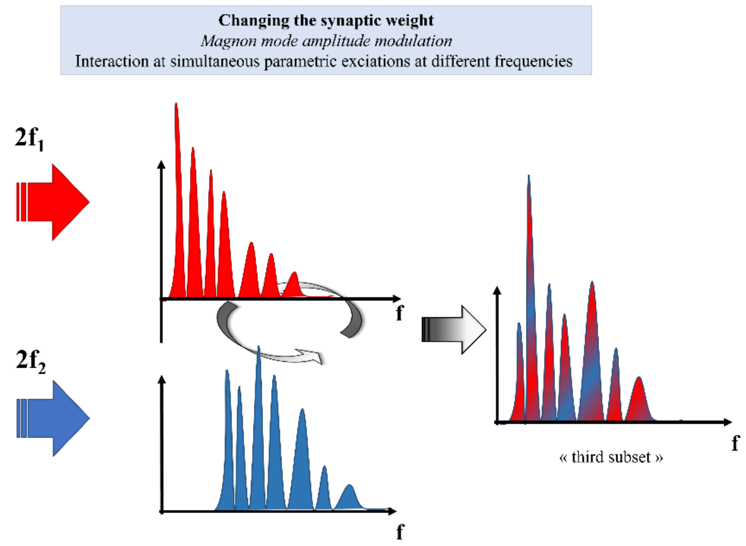


Figure 5: *Principle to change the synaptic weight in a k-NET based neural network by letting two (later N) magnon distributions parametrically pumped at two (N) different frequencies interact with each other. These interactions- in the nonlinear regime- will change the overall distribution of the amplitudes per populated mode and hence the synaptic weight which will allow for training.*

B: "Parametric programing with linear inputs"

This approach also relies on entering the nonlinear regime by parametric pumping. However, here the idea is to only use a single input frequency for the parametric pumping process to excite the spin wave modes in the YIG disk. (e.g., $2f_p$). That will put the system in the desired non-linear dynamical states with individual mode amplitudes, that is the synaptic weights depending on the choice of the value for $2f_p$. Then, to perform the targeted computation, additional single frequencies f_1, f_2 which are corresponding to selected resonance frequencies within the set of excited discrete spin wave modes, will be fed additionally to the system. This additional drive in the linear regime will have a direct impact on the values of the demagnetizing field. Correspondingly, the effective magnetic field acting on the spin wave modes will change by addressing one specific frequency. As a result, the amplitude distribution of the spin wave manifold originating from the parametric pumping will **change across the frequencies. Further, reading the output will be performed by observing the modification of amplitude of specific frequencies that are different from the input frequencies.**

Beyond monitoring the spin wave amplitudes, themselves with the known techniques (see **Figure 4**), another possibility to experimentally observe this type of modulation of the spin wave mode ensemble could be to investigate the response in the time domain of a single YIG disk as well. For instance, a sequence of RF pulses – with different frequencies – in the said linear regime would alter the response and hence allow to obtain insight into the programmability of our neural network with k-NET as well.

Here the parametric excitation consists of burst of RF pulse sequences that can be envisioned as the programing signal. The inputs of the k-NET device are then feed as frequencies (f_i) that resonate with modes (i) of the dynamical excited state. Compared to the first approach with two parametric drives, in this computation scheme, the spin wave amplitudes are then rather changed by using additional RF inputs (several frequencies in the linear regime). Specifically, this occurs at specific frequencies which are within the spin wave frequencies of the parametrically pumped system (see **Figure 6**).

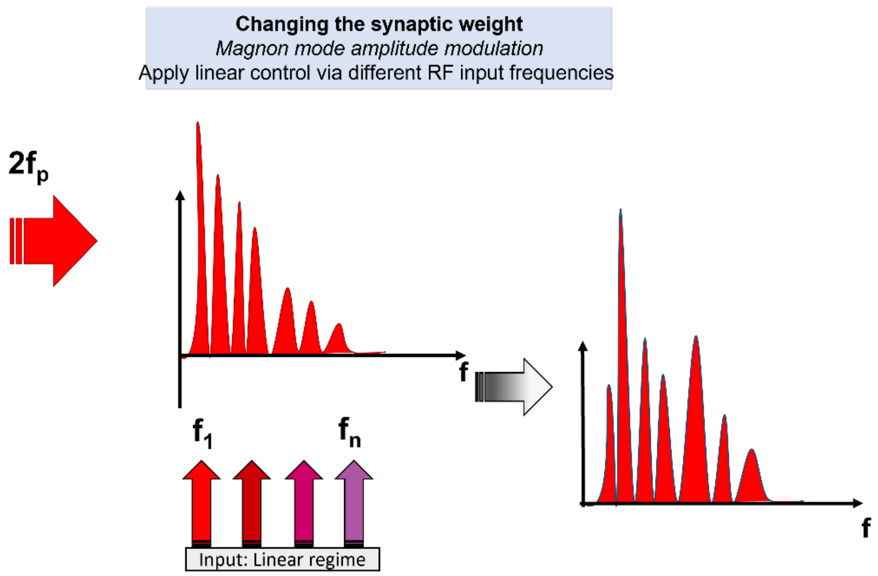


__Figure 5: Schematics of the second proposed approach of k-NET: The__ short-wavelength modes are excited by parametric pumping with a frequency $2f_p$ and are nonlinearly interacting with each other. An additional RF input with frequencies which corresponds to the individual resonance frequencies f1, …, fn of the total set of excited spin wave modes. These frequencies are in the linear regime and impact the demagnetizing field of the addressed spin wave mode and hence alter the effective magnetic field. In turn the amplitude per spin wave modes can be varied and hence the synaptic weights of our neural network changed.

5.4 Benchmarking methodology for k-NET proof of concept

For the future benchmark methodology, we will have to assess our proof-of-concept device on A. the comparability to existing approaches such as spintronic based approaches using STNO's and B. the uniqueness of k-NETs approach with respect on a large-scale integration. This large-scale integration assessment will be of course based on our experimental results and include remarks towards the scalability, device yield, the potential for the CMOS integration and economical aspects. The first market analysis which is part of this deliverable D4.2 contributes to it and serves as a first placement of the k-NET technology as well. Thus, at this stage of the project we can already prepare the final benchmarking. This is done by reporting on the first experimental results on changing the synaptic weights and how – based on that- we can identify one possible (of several ones, see below) classification task to perform the first proof-of-concept demonstration. As detailed out further, this will be vowel recognition.

5.5 First experimental evidence for the change of the synaptic weights

Example of measurements with a 3 µm (diameter) disk using approach A.

In the consortium, we have already started to perform first measurements using the MRFM technique on approach A using two parametric drives at frequency inputs $2f_1$ and $2f_2$ on a YIG disk of 3 µm diameter (**Figure 7 (a)**). Please note, that a change in the RF power also impacts the spin wave amplitudes, thus these measurements were performed both for the same power P=P(f1)=P(f2) (**Figure 7 (b)**) and subsequently for different powers (**Figure 7 (c)**). The spectra were obtained at a fixed externally applied field of 26.6 mT for the data shown in **Figure 7 (a)**.

In **Figure 7** we show experimental evidence (from MRFM measurements) that using two parametric frequencies (f_1, f_2) is enough to both change the spin wave amplitudes (**Figure 7 (b)**.) and to generate a response at other frequencies (**Figure 7 (c))**. Furthermore, this non-linear response is strongly dependent on the power of the excitation as can be observed by comparing **Figure 7 (d)** (low power) and **Figure 7 (e)** (high power).

Notably, one can also observe as conceptually explained before, that this type of experiments allows to change the amplitude of some spin wave modes in the disk and hence the synaptic weights.).

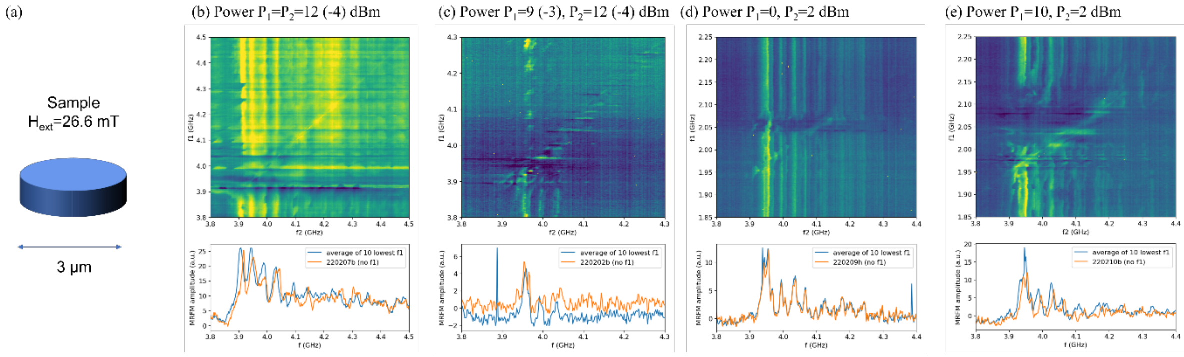


Figure 6: First experimental evidence using MRFM spectroscopy that the magnon population can be changed by injection additional frequencies. (a) Schematics of the utilized micro disk (b) and (d) Excitation with parametric drive and two input frequencies at the same power. The application of two parametric drives with different power (c) and (e) yields also changes in the spin wave amplitudes. The line plots below the spectra ((b)-(e)) show the average of ten lowest applied frequencies f_1 (blue line) and the same spectrum if only one parametric drive by turning off f_1 is applied to the system (orange line).

This experimental evidence demonstrates that we already have all the ingredients to perform a classification task for a neural network based on k-NET. By shifting the operation from real space to wavevector space, k-NET is not only a new hardware concept but also represents a generic paradigm shift for neuromorphic computing. As such, k-NETs approach can be in principle be applied to different classification tasks for neuromorphic computing ranging from handwritten digits recognition (cf. original proposal), pattern (image) recognition or vowel recognition. For instance, different handwritten digits could be assigned to different outputs using either proposed method A. or B., to perform the training. However, within the project one goal is to present a proof-of-concept for k-NET's operation. As we work naturally with a frequency distribution which can be tuned by the input frequencies, the power etc. (see previous section), currently the most straight forward approach is to demonstrate the proof-of-concept operation with vowel recognition. Other classification tasks are foreseen further down in the future. Vowel recognition directly operates with the frequencies and does not require any prior assignment such as for handwritten digits recognition. Furthermore, our spectra show similarities with the spintronic based approach using spin-torque nanooscillators from [15]. This- although operating in real space- is compared to other technologies (cf. Overview given in D4.1)- the one which resembles most. Thus, it will also allow us to perform the future benchmarking on another concrete example which can use to assess our technology. Then, the system's second generation could be also envisioned for other, more complex classification tasks, within the timeframe of the k-NET project.

Thus, together with the experimental evidence at hand we are confident that vowel recognition could be achieved with k-NET technology and will pursue this approach to make a first proof-of-concept demonstration that k-NET can be a game changer for neuromorphic technology.

5.6 Methodology for k-NET based vowel recognition proof of concept

Spoken vowels are characterized by formants. Formants are acoustic resonances in the vocal tract, that corresponds to the dominant spectral peaks at distinct frequencies in the spectrum envelope of a recorded voice. Formants are especially prominent in vowels. The lowest frequency of a formant is usually called F1, the second F2 and the third F3, however typically two formants are sufficient to identify the vowel. Moreover, each formant is associated to a resonance in the vocal tract, that is different vowels for instance. The different formants such as different vowels are separated in frequency (approximately 1kHz separation, which is in a typical range from 500 Hz – 3.5 kHz) and, for instance, characterized by twelve different frequencies (c.f. Ref. [15]).

The first preliminary spectra using two frequencies f_1 and f_2 -parametrically driving the YIG disk- with the same or with different input power (e.g. see **Figure 7 and Figure 8**) show spectra which resemble the one of coupled spin-torque nanooscillators [17] .

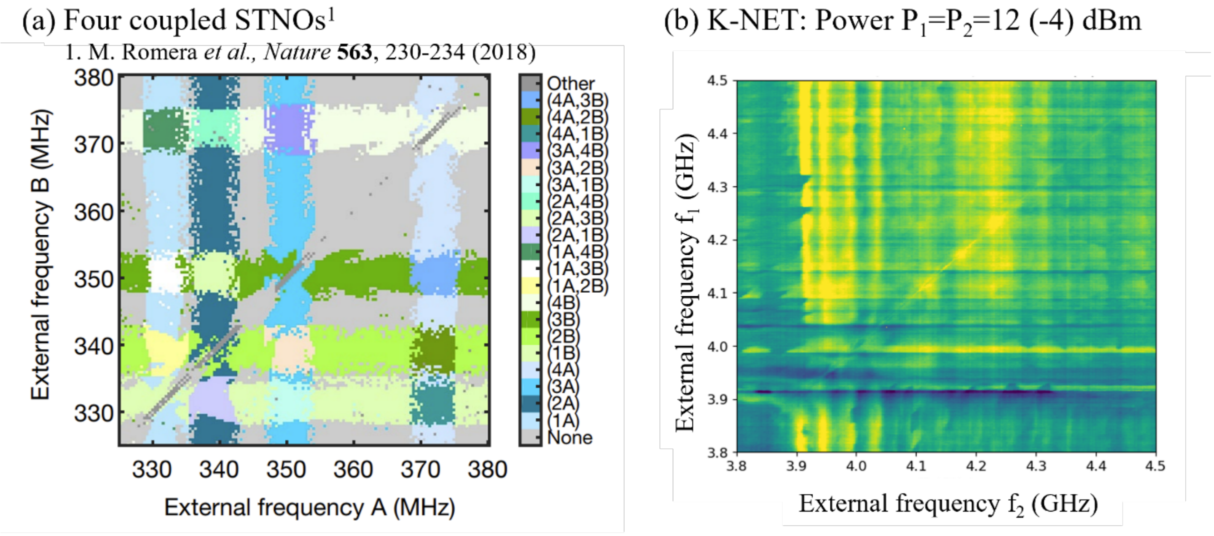


Figure 8: *Qualitative similarity between the spectra from a system of four coupled STNOs used for vowel recognition[1] and the first spectra from K-NET using two parametric drives $2f_1$ and $2f_2$*.

Although, the approaches are conceptually different – four coupled STNOs vs. nonlinearly coupled spin wave modes in one micro disk and wavevector space operation (k-NET)-the shared physics of non-linear magnetization dynamics based on the LLG equation allows to draw some analogies. Naturally, this also indicates that one can find a benchmark methodology for the first k-NET proof-of-concept device to demonstrate vowel recognition. Furthermore, it also allows a direct comparison not only to general approaches to neuromorphic computing but also to spin-based approaches for neuromorphic computing. This will further contribute to identify k-NETs technology as a game changer.

Therefore, the concept which is proposed here, follows the experiment for vowel recognition from Ref. [15], while aiming to adapt to the specifications needs for k-NET approach. An adaption during the process towards the final demonstrator will be made if necessary. However, the rich number of degrees of freedom to control the spin wave modes' dispersions (& amplitudes) of the k-NET samples such as the externally applied field, the power, the exact geometrical size to name only a few, minimizes the risk drastically and allows for said, eventual adjustments.

In the k-NET conjuncture, the spin wave modes that is k-NETs neurons operate at frequencies around 3-4 GHz from Ref but comparable to more recent works [18], [19]. As we currently envision to operate similarly to Ref. [15] to address the formants associated to the vowels, the input frequencies will require up conversion or need to be decomposed in linear combinations of the number of frequencies which are used to characterize one vowel.

For instance, Ref. [15] used a subset of the Hillenbrands database where twelve different frequencies characterize one vowel and in total 37 different female speakers pronounce seven vowels.

Once the decomposition (linear combination) has been defined, the classification task for vowel recognition with k-NETs approach can be performed as schematically depicted in **Figure 9.**

Note, that here the schematics is using the "All-parametric" approach A but can also be replaced by approach B to use a linear input. The change is only in the way we control the spin wave amplitudes and resonance frequencies, the concept remains the same.

Then, the result from that classification task will be compared to the spin-based result from Romera et al., standard neural networks and CMOS operation for parameters such as the classification efficiency or the energy consumption. This will also allow to benchmark the new technology against

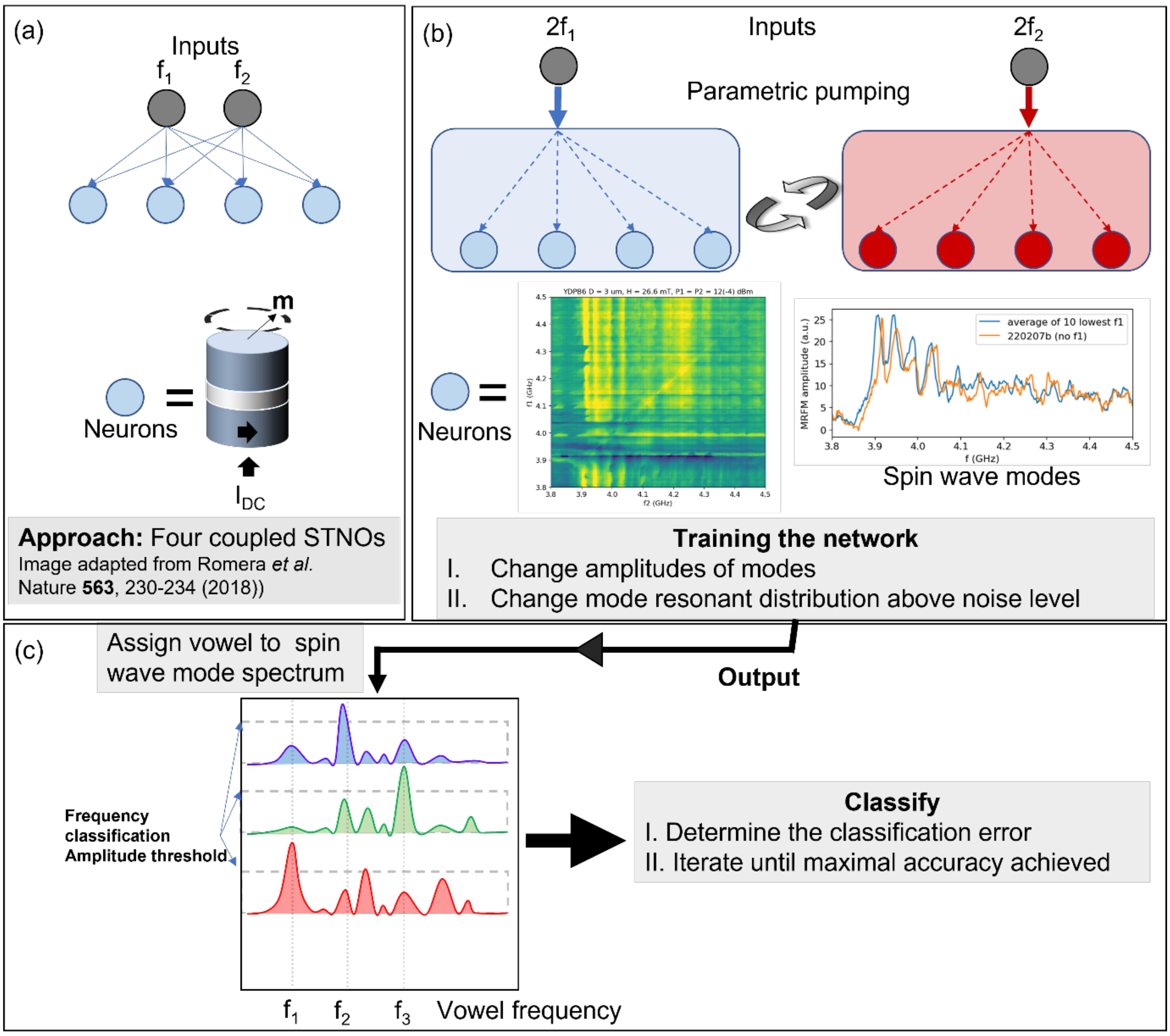


Figure 7: Concept for vowel recognition with k-NET for a future proof-of-concept device. *(a) Comparison to a spin based neural network for vowel recognition employing four coupled spin-torque nano oscillators (STNOs)) (Romera et al., Ref. [1]). Each STNO acts as a neuron and is interconnected to two input frequencies which are used to map the output to the input and validate the successful training. (b) Equivalent picture for the k-NET approach. However, here there is a "bath" of neurons as one neuron corresponds to one spin wave mode. No wiring accepts the individual frequency inputs (number of inputs corresponds to the number of vowels to be classified) is required. The spin wave modes undergo nonlinear interactions and when an additional frequency is turned on, first data from the CEA partner (courtesy G. Loubens) using the same power at both inputs show that the amplitudes and the resonance peaks change. This demonstrates that training the network is possible. Contrary to a single frequency, we assign one spectrum- specific distribution of the amplitude to each vowel with a corresponding frequency dominating the spectrum as a peak above a previously set threshold (c). This is contrary to the approach of Romera et al., we use the entire distribution in k-space and let it interact. We use this interaction for changing the individual weights but do not address one specific mode. Then the threshold determines the frequency output which is compared to the desired input and classification is taking place. In an iterative process- that is using the backpropagation method, for instance- the task is performed until the maximal accuracy is reached.*

existing approaches. The future experiments will allow to give some real numbers but already now some points can be pointed out which also underline the potential of k-NET. First, the comparison of the schematics of the neural network shown in **Figure 9** (a) from Romera et al. and the one proposed for k-NET in the top part of **Figure 9 (b)** indicate clearly the strongly reduced number of wiring and interconnections. Further, only radio frequency inputs are required and no additional DC signals. This will allow **A. smaller scales for a future chip and B. even less power consumption** than the results from Romera et al.

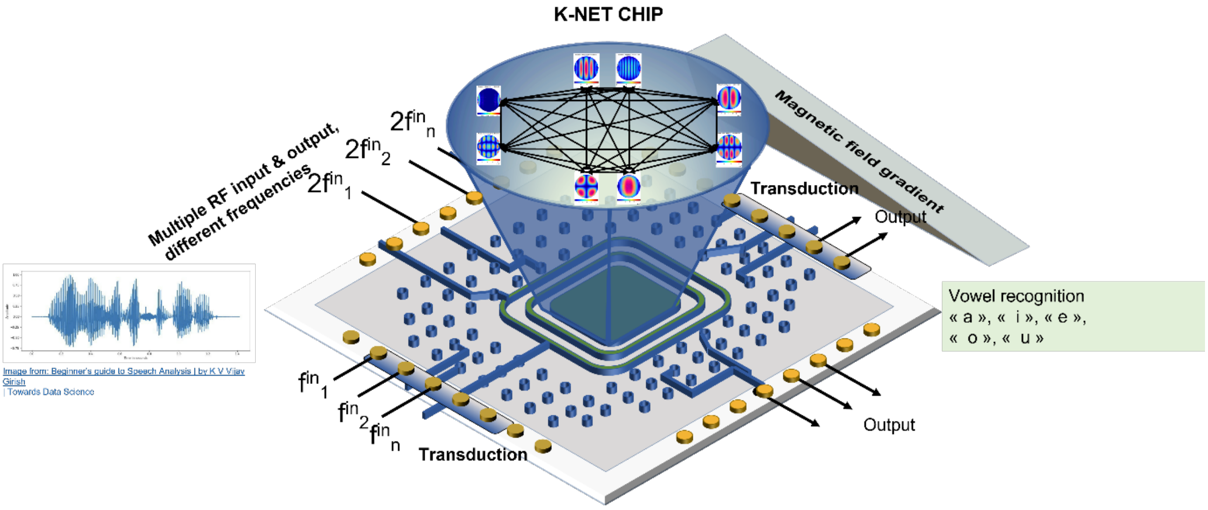


Figure 10: Vision of the k-NET device in form of a chip, exemplarily showing the classification task of vowel recognition for the proof-of-concept device. *It can represent also a pre-processing unit in a bigger neuromorphic chip to deliver "pre-trained" data to the input of the neuromorphic computer which will then run a software afterwards for the AI. The multiple frequency inputs (left and bottom) can be provided by a single line via arbitrary waveform generation. Different antenna and waveguide structures on the k-NET chip provide different means to read out the system. The disk matrices operating as neurons are illustrated by the violet dots placed on top of the feedlines (dark yellow). The blue disks are a schematical representation of a typical chip design.*

Second, a small k-net chip can serve as a pre-processing unit (see market analysis) to pre-train data sets before they are given to a software or an architecture which might be CMOS based and could serve as the input for the computational classification task itself. Thus, the k-net architecture would be able to compute a predefined output. Hence, a k-net chip could be a central hardware component for artificial neural networks for neuromorphic computing. This could be in line with a current need for CMOS compatibility. This is because, to date, hybrid systems consisting of cmos & new technologies currently have a higher potential to reach industrial maturity than the new approaches alone. As can be seen from the previous deliverable **D4.1** to show the *state of the art for neuromorphic computing,* most new approached beyond CMOS have not yet reached the level of maturity to operate fully independently. This could be a starting point of k-net to enter the market, establish a hold in the market of neuromorphic computing as such "universal" pre-processing unit and then grow from that position. **Note, that in our system, it is also possible to perform training during the operation by tuning the frequency input such that we obtain the desired output. This is different to reservoir computing where the system evolves in a "black box" manner and is not manipulated.**

5.7 Concluding remarks on k-NET based devices

Based on the concept shown in **Figure 9** and the specific design of the k-NET sample for the RF antennae and the disk geometry (see reports and deliverables from the consortium), a future k-NET chip could be envisioned as shown in **Figure 10**. In principle, the chip only requires a single RF line for input and output signals and small permanent magnets- if it could operate at one field value or a permanent field gradient which is placed in close vicinity to the disks (see also **Figure 10** for the schematics). The design of such a chip in this manner will also ease the commercialization as it can be sold as a "all-in-one" device while being compact and consuming little power. If in addition the magnetic material (YIG) could be changed to be grown on a semiconductor our approach could be also more integrable to CMOS based technology. Furthermore, the chip itself can be upscaled by increasing the frequency inputs or by connecting several k-NET chips which each of them individually solve one part of a more complex classification. For instance, such as by using multiple disks, we could connect one disks output to the other disk's input. Note, that the promising first results have been so far obtained and that further specifications or concrete numbers require further experiments and simulations with the involvement of all partners.

However, at this point of the project and with concrete vision of the first k-NET device, it is now possible – and necessary for the future integration of k-NET into the market of neuromorphic computing to discuss in more detail the neuromorphic market and its estimated development for the next decade. This will also show that the development of a new technology like k-NET is not only timely due to a rapidly evolving, young and dynamic market where final key players are not yet fully set but also has direct economic and hence political and societal impact for the European Union's market.

6. Analysis of the market in which k-NET will operate

6.1 Design of the analysis

To date, neuromorphic computing and artificial intelligence (AI) markets are expected to have a high growth within the next decade due to the combination of improved computational power and increasing demands from digital (big data, IOT) and across "classical" key industries such as the automotive sector, aerospace and defense, consumer electronics, healthcare or piping for new generations of "intelligent systems". Several economic reports state that the market for neuromorphic computing is expected to grow with a CAGR (**C**ompound **A**nnual **G**rowth **R**ate) of 89.1 % between 2021 and 2026 (Neuromorphic Computing Market Size & Share | Industry Report, 2021-2026 | MarketsandMarkets™) . More conservatively, the neuromorphic chip market is expected to grow with a CAGR of 47.4 % in the period of 2021-2026 (Neuromorphic Chip Market | 2022 - 27 | Industry Share, Size, Growth - Mordor Intelligence). Accordingly, the computing (chip) market was valued USD 22.5 million in 2020 and projected to be worth 550 million-8 billion (source dependent) (333.6 million) by 2026. The increased activity of R&D for neuromorphic computing and foundations of spin-offs is also reflected in the emergence of new start-ups among them several are located in Europe as will be elaborated further below.

Hence, the main purpose of this section is to identify the main players and trends in product development in the neuromorphic market.

A complete and 100% exhaustive study is not relevant at this very early stage of the project because the market is extremely immature and evolving really fast. The paths taken by the technologies are dependent on disruptive innovations and scientific evidence emerging from new methods. On the other hand, it is important to know the main trends that are emerging by focusing on a few interesting examples, the main players involved in the technological race and the needs of end-users.

In addition, much more comprehensive market analyses have already been carried out. Major consulting groups with a reputation for assessing IT technologies have already produced comprehensive reports with a business focus. For instance, Mckinsey ("Artificial-intelligence hardware: New opportunities for semiconductor companies", [20]) integrates the study of neuromorphic elements into more general AI elements but other studies focus on neuromorphic. This is in particular the case of a study by Yole: "Neuromorphic Computing and Sensing Market and Technology Report 2021" (Yole consulting) which is for instance cited several times in the roadmap on neuromorphic computing ("2022 roadmap on neuromorphic computing and engineering", Dennis V Christensen et al.).

The Human Brain Project (HBP) funded by the Commission has also produced two public deliverables for the neuromorphic community and broader public:

- a general reference study on neuromorphic computing: "NEUROMORPHIC COMPUTING: Concepts, actors, applications, market and future trends")

- a deliverable more focused on SNN but which contains extremely interesting elements on the different trends and applications: "Recent Advancements on Deep Spiking Neural Networks algorithms and their implementation on neuromorphic chips: an emerging new market)

The purpose of these deliverables is to avoid having to do the very heavy work of a general market assessment. This can also help to attract the interest of investors and direct the work of the community towards applications with a realistic market.

The work presented in this section is a synthesis of the most interesting information contained by the above sources, enriched with some other elements, and updated as much as possible with more recent facts. The aim of the overview, which is more general than the use-case, is to provide a global understanding of the market in order to better monitor the market potential, which can sometimes be lacking in the theoretical field.

The end of this section focuses much more on the potential that k-NET could address with the use-case. This, in order to justify or not the relevance of the use-case not technically as presented in the first part, but in terms of market opportunities.

6.2. The emergence of Neuromorphic Computing in the context of the AI boom

1.1) AI market: growth and estimated share in the coming years

Specialists have very close estimates of the AI supported semiconductor market volume. As displayed in the diagrams in **Figure 11**. The market is expected to double from around $30 billion in 2020 to over $60 billion in 2025.

Another important element to note is that the **AI-supported market is expected to grow five times faster than the conventional semiconductor market**.

The market is still mainly governed by the AI-semiconductors although other approaches exist (see D4.1). The market itself is segmented between datacenter or edge architectures where each branch is again segmented according to the type of desired AI-operation, if it is performing inference or training. As one can infer from **Figure 11 (c),** in terms of the different types of AI accelerators, CPU (**C**entral **P**rocessing **U**nit) and GPU (**G**raphics **P**rocessing **U**nits) currently have the largest share of the market, although new technologies are gaining momentum. By 2025, ASIC (**A**pplication-**S**pecific **I**ntegrated **C**ircuit) technologies are the most promising trend, although the GPU will also continue to grow. The synergies between ASICs and neuromorphic computing are very promising and are a dynamic field of study. One example is the partnership between BrainChip (Akida neuromorphic chip) and MegaChips, one of the world leaders in the ASIC field. The other major distinction is between edge-computing and data center architectures (clouds). As can be seen in **Figure 12,** the edge market is less developed at the moment, but the next few years will see the emergence of a much larger edge market, driven in particular by the need for security and cost efficiency. In-situ processing is de facto much less energy intensive. Edge AI emerged from a desire to integrate artificial intelligence as close as possible to sensors or connected objects (**IoT**, **I**nternet **o**f **T**hings). The advantages are multiple such as no need for permanent internet connectivity, data confidentiality, reduced latency.

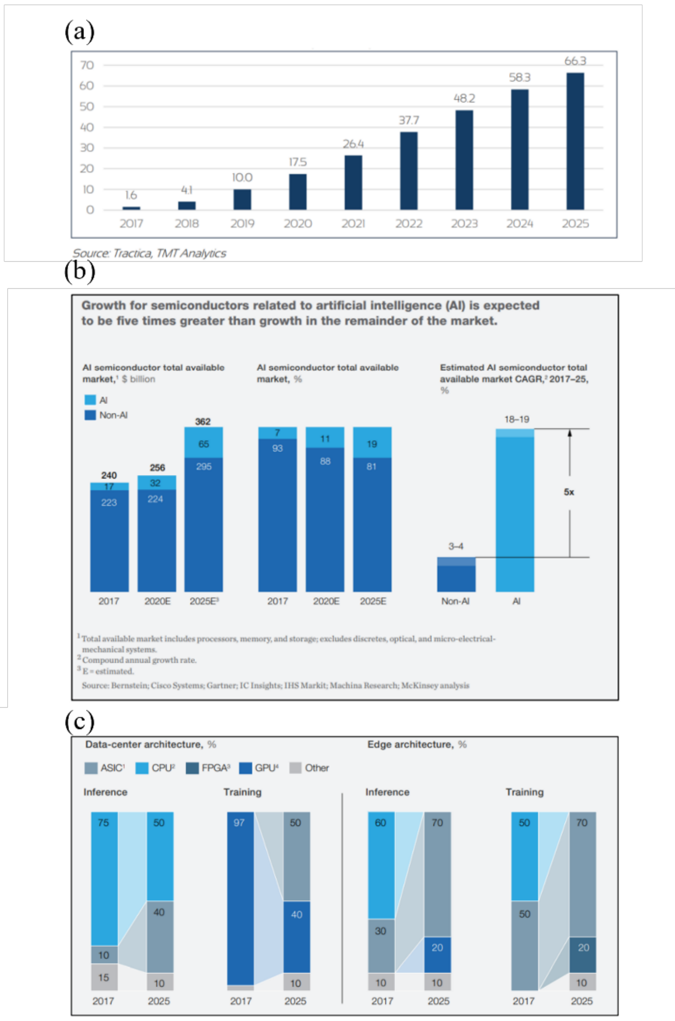


Figure 11: *Growth of the AI-semiconductors market volume (Kennis, 2019) (b) Market of AI and Non-AI semiconductors (Batra et al. ,2018). (c) Market segmentation for the AI-semiconductors market. The segmentation is first by the markets for either datacenter (cloud) or edge AI architecture, and then by the specific AI operation which is Inference or Training. The market share of the individual semiconductor technologies (ASIC, CPU, GPU, FPGA and GPU) is shown*

Edge AI allows part of the IT processing flow to be moved directly to the connected objects, thus reducing the use of the cloud for processing-related tasks to a minimum. The edge AI is really going to be the first catalyst for the emergence of neuromorphic technologies. There are still many bottlenecks to go beyond the classic cloud and data farm computing models in the short to medium term, although work is already underway to significantly scale up neuromorphic devices.

We will discuss edge computing in more detail in the section on applications.

Figure 12: *Market overview of semiconductors for Data Center architectures and Edge AI (Batra et al. 2018)*

6.3 The place of neuromorphic computing in the future of AI

a) General outlook for the neuromorphic market

The market is currently extremely small (or even almost non-existent) since it does not even represent 1% of the AI-supported hardware market. However, it is expected to grow drastically over the next 10 years.

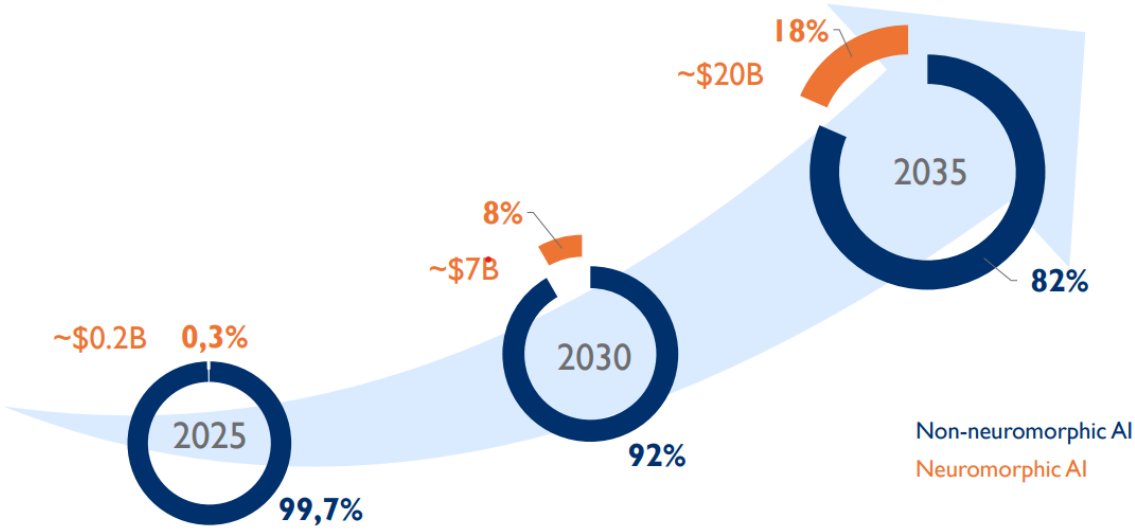


Figure 13: *Forecasting on the development of the AI market (Yole consulting, 2021). From to date to 2035, the market share of neuromorphic computing is predicted to be a substantial part of the AI market, which would be an increase by 60 of the market seen by 2025.*

Although studies do not predict the same exact size of the market and the moment when the take-off will start, the general trend towards a significant increase in market share is indubitable. This potential has been recognized by both the scientific and economic specialists, who are enthusiastic about the development of neuromorphic technologies. This trend is indeed also reflected in the increasing efforts (research volume, funding and investments).

This steep gain in market share can in particular be attributed to the significant advantages neuromorphic AIs offer compared to conventional AI accelerators. Among them are a better energy efficiency and improved theoretical performance. More importantly, they can also handle both AI inference and training in real-time. Moreover, edge training is possible through neuromorphic chips [21]. However, as stated earlier, learning methodologies should be improved to increase their accuracy.

Yole and TMT Analytics expect that the market size of neuromorphic chips can reach a billion-dollar around 2025 with a growth rate of 51% between 2017-2023 (Yole Development, 2019. Neuromorphic Sensing and Computing 2019; Market and Technology Report). By 2035, the Yole report predicts that it will represent a share of about 18% of the total AI market worth about $20 billion.

One can partly infer on the dynamics and controversial predictions of the neuromorphic computing market as, for instance, in Ref. [21] the authors predict a dominance of neuromorphic computing in the AI-accelerator market in the early 2030s (see **Figure 14**). These optimistic estimates must of course be tempered by the fact that they depend on the success of the first neuromorphic applications on the market and the overcoming of the bottlenecks mentioned.

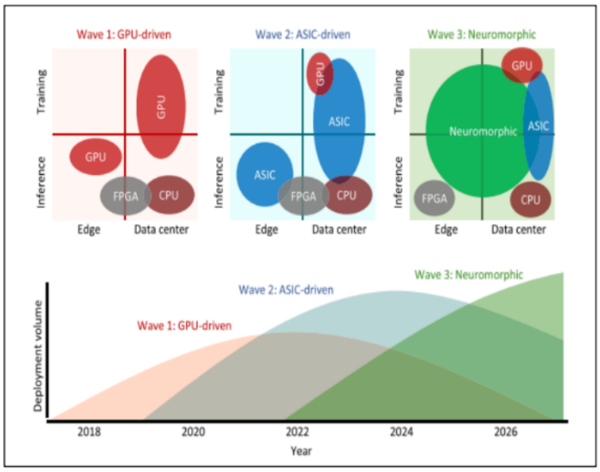


__Figure 14:__ Expected waves for semi-conductor dominance in the area of AI (Kendall & Kumar, 2020)

Note, that the absence of complex wiring and the unique approach of k-NET to translate the operation from real to wavevector space is also one of its biggest assets to overcome current bottlenecks in the neuromorphic computing sector. In the following, we further outline the current developments of the neuromorphic computing market in general and show how the paradigm change made with k-NET can lead to a more universal impact on neuromorphic computing. Although we focus on vowel recognition for the proof-of-concept classification task with k-NET, other classification tasks and a combined inference and training would be possible. Thus, k-NET has indeed the potential to be a game changer.

Another shared opinion among specialists is that neuromorphic technologies will be at the heart of the development of edge computing. This will even be more and more relevant in the context of IoT (Internet of Things) where networks can be overwhelmed by irrelevant information. Regarding k-NET, the integration of k-NET in the edge revolution remains conditional on certain factors, notably the level of complexity and speed of the needed processing. k-NET based devices would be particularly competitive if a high processing power is needed.

6.3. Mapping of the main players in neuromorphic hardware:

1) Overview:

The most advanced countries and currently dominant players are China and the United States. The United States is led by Intel and IBM, which decided to create neuromorphic communities around their chips and were the first major movers. However, China is the leading country in terms of patents. Surprisingly, large US companies like Apple have their neuromorphic patents registered in China. One of many examples of Chinese ambition is the recent acquisition of the Swiss start-up aiCTX by the Chinese company SynSense. aiCTX was one of the neuromorphic start-ups that raised the biggest hopes among the neuromorphic players. The CEO of SynSense has announced that he wants to create the largest neuromorphic ecosystem in the world. It is therefore reasonable to anticipate that we will see much more patents from Chinese companies soon.

Europe is far from being left behind. It is the continent with the largest number of interesting start-ups in the field of neuromorphic hardware and taken as a whole it is the 3rd region in terms of patents. The initial European efforts such as with the Human Brain project **(HBP)** which resulted in one of the largest neuromorphic computers to date – BrainScales- are reflected in the fact, that among the 10 highest rated start-ups world-wide for neuromorphic applications are two European ones. These are namely **Innatera Nanosystems,** a Dutch company using SNNs and **INSTAR Robotics**, a French company which employs neuro-inspired robots for agriculture. Outside of the EU but in the European market are a British company in the healthcare sector namely **Cryx Medical for** Neuromorphic sensors, better medical devices and bioelectronics, and **iniLabs a swiss**, spin-off of University Zurich and ETH for dynamic audio sensors based on SNNs and address-event-representation.

Moreover, the HBP is certainly the most ambitious international project in neuromorphic computing. It is not only focused on computing. It explores cognitive mechanisms, medical applications, etc. It also allows the constitution of a European community, datasets and tools that can be unlocking factors for innovation. The HBP also provides a pool of potential partners.

Although Europe is currently lagging behind in the semiconductor market and the electronics industry in general (just under 10% of the microchip market), it has greater ambitions for the future IT revolutions and the possibility to take the lead in neuromorphic computing is considered as a great opportunity.

In this mindset, the announcement of the Chip Act [22] is a natural step in developing a European technology. This act is comprised of a €43 billion worth investment to reach 20% of the world market by 2030. In view of the plethora of open questions and challenges, the Chip Act includes both funding for fundamental research and also a detailed plan for setting up a European ecosystem for neuromorphic computing:

I. **Invest** in next generation technologies identified as key for economic and political independence
II. **Establish** EU-wide access to design tools and pilot lines for prototyping, testing and experimenting with advanced chips
III. **Develop** a certification procedure for energy-efficient and reliable microchips to ensure the quality and safety of critical applications
IV. **Create** a more investor-friendly framework for setting up production facilities in Europe.
V. **Help** start-ups, growth companies and innovative SMEs to access equity finance.
VI. **Foster** skills, talent and innovation in microelectronics.

The announcement of the plan can be a real opportunity for the next steps to be taken after the end of the k-NET project since: operating in k-space and using the as inputs radio-frequency signals in the GHz range, k-NET brings all prerequisites to be employed for signal processing and hence IT & telecommunication and aerospace & defense.

Furthermore, the presence of THALES as a stakeholder for RF applications and defense, will support and accelerate the incorporation of k-NET into the market. Also, this allows to gain market shares in this area of neuromorphic computing in the next years thus reenforcing the market "made in Europe". Although all markets are expected to grow in the coming years, the APAC (Asia-Pacific) market is yet expected to grow the most, boosted by the strong economic growth of China and India and common interests in wearable technology and machine-to-machine communication. The European market, however, is only expected to undergo a growth on the intermediate level, if it is benchmarked against the other economical areas such as Northern America and APAC. In view of the societal and political challenges, we will be facing in the following decade(s), pushing the autonomy and the power of the European market is inevitable to maintain the current societal and economic conditions. This is reflected also in the Chip Act. Correspondingly, by opening a new axis of neuromorphic computing with first envisioned concrete applications in future central sectors of neuromorphic computing, k-NET can - as a fully European consortium- strongly contribute to that.

2) The most prominent players

In this section, we will not discuss in detail the technologies developed by the institutions (laboratories, companies, etc.). The elements we highlight are in particular the interest aroused in the community and investors, some technical characteristics of the technological development scheme and finally the potential markets or the expected uses of the technology.

The market is above all characterized by its highly atomized character, which is totally different from the conventional semiconductor market of course (a much older and highly concentrated market). It is impossible to talk about all the chips and all the start-ups because there are so many. The two HBP market analyses mentioned above include tables gathering many more players. Here we focus on the most important ones with more up-to-date data and enriched with some names.

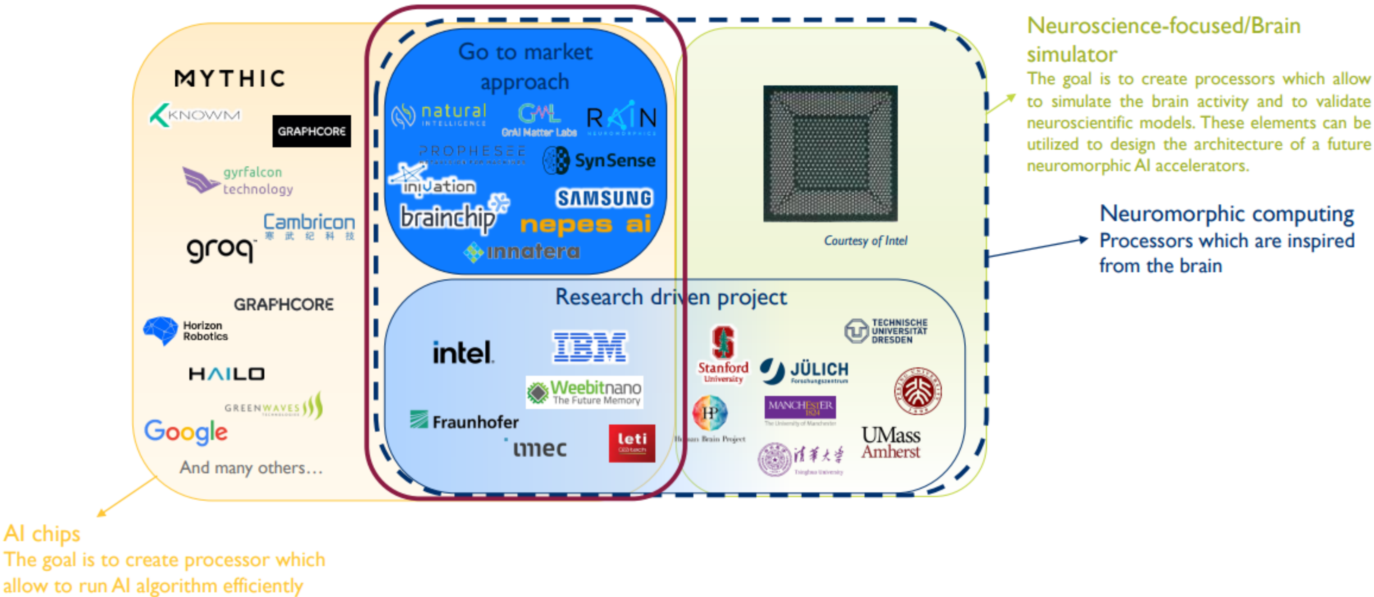


Figure 15: Main companies and research driven players for the neuromorphic computing market. (Source: Neuromorphic Computing and Sensing Market and Technology Report 2021, Yole consulting)

<u>A. IBM and Intel (first big movers):</u>

A.1. **IBM**:

IBM was the first big company to develop its neuromorphic chip. TrueNorth was one of the first chips to show better qualities than conventional systems. The chip has for instance proven usefulness in relation to low energy consumption compared to GPUs [23]. However, the device is on-chip programmable so it can be only used for inference. This is a major disadvantage for the on-chip training research and at the same time limits the usage of the chip in critical applications (such as autonomous driving which needs continuous training). IBM is carrying out important research work in the field of emerging memories in particular. The first version of TrueNorth had no integrated memory. However, a new version of IBM's neuromorphic chipset tested in 2018 has integrated PCM (Phase Change Memory) memristors. This further improved the energy efficiency of the whole package, but with only 204,900 synapses to begin with. The tests were carried out on a writing recognition algorithm applied to the standard MNIST base. This chipset performed 29 billion operations per second per Watt consumed, slightly less than the original TrueNorth chipset.

One IBM'S objective is to use the chip on cognitive applications such as robotics, classification, action classification, audio processing, stereo vision, etc. However, at the moment the TrueNorth is not for sale for end-users, being only used for research purposes.

A.2. **INTEL**:

Intel released its neuromorphic chip "Loihi" in 2018 [24]. The chip is digital and on-chip programmable. This gives flexibility to the chip so that researchers can work on a variety of learning methods, from DNN to SNN conversions, native SNN, etc. Like IBM, Intel is also investing in the commercialization of the neuromorphic chips and learning methodologies.

More recently, the company announced a new version of its chip as well as Lava software (an open-source software framework for developing neuro-inspired applications) [25]. Intel claims that Loihi 2 enables the architecture to support new classes of neuro-inspired algorithms and applications, while offering up to 10 times faster processing, up to 15 times greater resource density with up to 1 million neurons per chip, and improved power efficiency.

Intel is specifically interested in cognitive applications. They expect to have a killer-app to solve real-world problems. And they believe that such an app should be related to the robotic sector, which is the one where the neuromorphic chips can more markedly express their competitive advantages, i.e., a "real-time inference with low energy consumption".

Note: It is merely impossible to cite all the projects developed by the major electronics groups because they are all at least minimally interested in hardware for neuromorphic computing. Samsung, for example, has chosen to approach neuromorphic innovation essentially through sensing.

B. The most advanced commercial chips:

B.1. Brainchip:

The Australian company recently released the second version of the Akida neuromorphic system-on-chip. Their inference and training chip is claimed to be the first fully versatile, reconfigurable and scalable commercial chip. Brainchip promotes its chip for facial recognition, object detection and classification or autonomous learning technology, keyword retrieval and speech classification among others.

In order to increase the volume of potential customers, they also sell the intellectual property licenses of their designs (Mankar, 2020). The company has also announced two major partnerships [26], [27]:

1. In May 2022, a technology partnership with Japanese ASIC company Megachips. The aim is to provide Akida advanced, ultra-low-power learning-on-chip and artificial intelligence capabilities as embedded technology in Megachips' ASIC solutions.

2. In June 2022, a technology partnership with Prophesee (a French start-up leader in neuromorphic sensing) to provide next generation platforms for OEMs looking to integrate event-based vision systems with high levels of AI performance coupled with ultra-low power technologies.

They also have an older partnership with NVISO (a Swiss company specialized in edge computing) to target battery powered applications in robotics and mobility/automation.

The impact of the Akida Brainchip needs to be monitored closely. The value of their shares on the Australian Securities Exchange (ASX) increased by 973% last year, with a total market capitalization of A$749.7 million (Yahoo! finance, 2021 and Stocklight, 2021). They have raised about $30 million and Brainchip definitely seems to be the most advanced company in the commercial race.

B.2. SynSense (former aiCTX):

In May 2020, the Chinese company SynSense acquired the Zurich based company aiCTX. SynSense develops neuromorphic hardware and software solutions by leveraging the work of the Institute for Neuroinformatics at ETH Zurich. They have modified and improved this original chip into different purposes. DynapCNN manages one million impulse neurons and four million parameters adapted to very low power embedded applications. In particular, it is used in computer vision applications for real-time event detection with a very low latency of 5 ms. It supports all types of convolutional neural networks. The ASIC type chip is manufactured with the 22 nm technology-node and exhibits a footprint of only 12 mm^2. DYNAP-CNN is adapted for Spiking Convolutional Neural Networks which makes it the best candidate for visual processing applications via input from event-based vision sensors.

They also propose the DynapSEL which is adapted for various neural networks, notably recurrent or reservoir neural networks and for applications in health and robotics. It includes a thousand pulse neurons and 80,000 configurable synapses. DYNAP-SEL enables on-line learning and real-time implementation of large-scale models with its large fan-in and fan-out network connectivity. The latest available chip DYNAP-SE2 is suitable for real-time applications in the area of robotics and medical health applications (not many other information at the moment). Concluding on that, used as the basis of the Chinese neuromorphic ecosystem (and surely highly supported nationally), it is a player to watch [28].

B.3. GrAI Matter:

The **French company** is designing a processor based on a neural network architecture, digital but asynchronous, using spiking neurons. They developed a first sparsity native AI-SOC (system on chip) where they aim to use edge computing mostly for audio and video processing. Their ambition is to integrate a million neurons in a square centimeter, consuming 1 W and programmable in Python.

They raised $30 million, and they have obtained a million dollars in funding from DARPA for an FPGA demonstrator that is already working. The target markets are autonomous vehicles, the connected home and health [29].

B.4. Rain:

Rain is an American start-up company that is developing a "Memristive Nanowire Neural Network " chipset architecture that would be fast, powerful and highly scalable. The neurons are connected to each other by nanowires arranged somewhat randomly to link the neurons together. They use deep learning with the "reservoir network" technique. It is an original approach [30].

Rain recently raised $25 million, bringing the total to $30 million. The applications are not really detailed at the moment, but the company is really attracting a lot of interest among investors and scientists alike.

B.5. AnotherBrain:

It is a **French startup** that has raised 30M€. The architecture of its chipset is not documented at this stage. The concept would be very different from all other neuromorphic chipsets, with the advantage of a faster training process requiring less data and energy. The startup is targeting industrial and automotive applications. The principle seems to be handcrafted feature-based learning to detect anomalies in images [31].

B.6. Other research chips:

Other chips are currently geared towards research, such as Loihi (Intel) and Truenorth (IBM).

The most important research chips are:

I. **SpiNNaker** which is a digital, on-chip programmable hardware designed by the University of Manchester. SpiNNaker was the first of such type of on-chip programmable digital chip, so a wide variety of research has been conducted around it. It aims to simulate the operation of a billion neurons. It is based on a hardware architecture with 18 32-bit ARM cores of 18,000 neurons per chipset [32].

II. **BrainScaleS** is an analogue, on-chip STDP programmable hardware designed by the Heidelberg University. BrainScaleS is designed for brain-research applications to study neuronal activities of biologic structures. It is an accelerated system that runs 10000 times faster than biological speed [33]. However, the analogue structure and acceleration (signal loss during such a rapid transmission) causes noise in signals and decreases the accuracy compared to other neuromorphic digital chips [33].

III. **Braindrop**, launched in 2019, which is a subthreshold analog mixed-signal neuromorphic hardware built by Stanford University. They design chips for the research purposes, rather than commercial. Stanford University claims that their chip consumes lower energy than the Intel Loihi and the "energy-efficient" AI accelerator of the Tesla chip [34].

Braindrop's research has recently evolved into a commercial chip developed by the Femtosense spin-off which is currently only used for audio and sound classification.

IV. Many other research chips exist of course such as **CEA Leti's "SPIRIT"** [35] or the promising **Darwin chip** from Zhejiang & Hangzhou Dianzi University [36].

6.4. Potential Applications and Trends

1) Market segmentation

The market segmentation is important as well to assess where the k-NET technology can enter and have the highest, disruptive effect in terms of a game changer. Despite these really recent and encouraging developments from fundamental research and new companies, the neuromorphic computing market is still a niche and just starting to form. Although some companies such as Intel currently share higher market holds than others, there is a lot of movement in this market. This change is expected given the dynamical development which is foreseen for the neuromorphic computing market. Recent studies point out that the currently leading contributors in this sector are pursuing market development strategies such as setting up collaborations, product innovation and intensified R&D actions. Therefore, contrary to a consolidated market the market concentration is still considered to be at the medium level. This leaves lots of opportunities for new players such as a possible one based on k-NET to enter this market (**see Figure 16-17**). Hence, a high impact of the new k-NET technology is reasonable.

The market segmentation per (leading) company is shown in **Figure 16** [37].

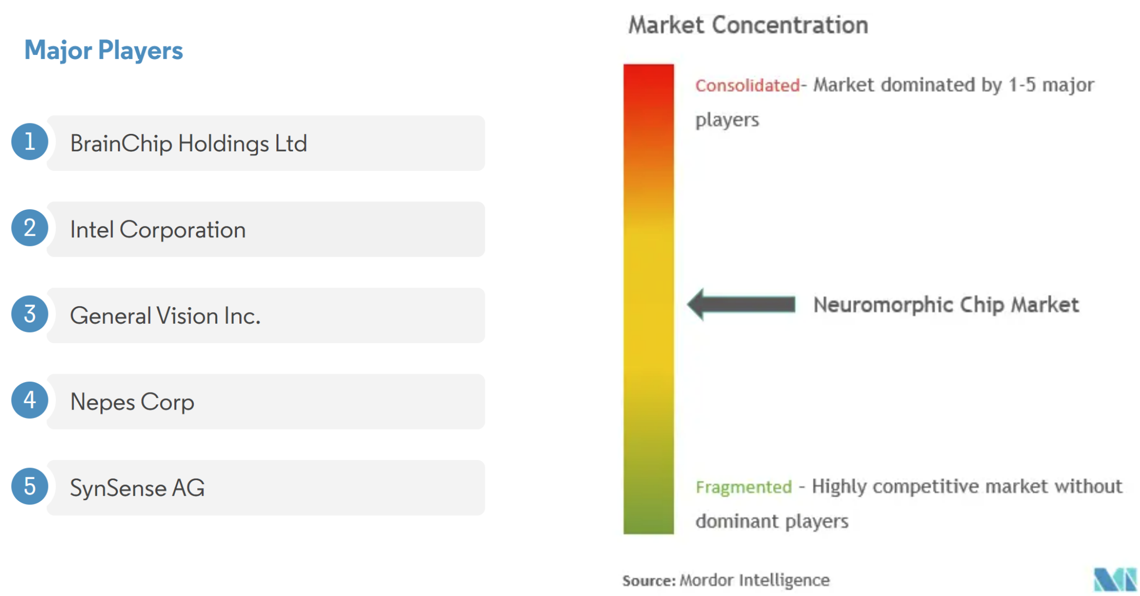
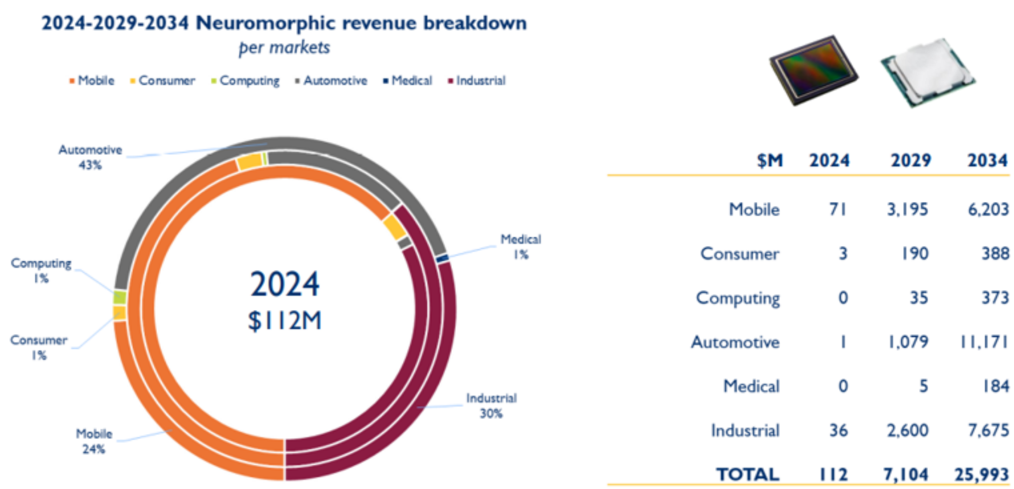


Figure 16: *Market segmentation of the neuromorphic computing market per (currently leading) company. It shows the market is segmented at a medium level and about to form, thus yielding huge potential for new ideas such as k-NET to enter the market at this stage.*

Note, that following current analyses for the development of the neuromorphic market, most reports state the complexity and limited density of current market solutions as one of the main hindering factors for true commercialization of neuromorphic computing and making it to leave its niche position

However, in terms of the applications – especially since k-NETs approach is more versatile and could be used for different classification tasks- a market segmentation per application area and the revenue breakdown are also important.



$M	2024	2029	2034
Mobile	71	3,195	6,203
Consumer	3	190	388
Computing	0	35	373
Automotive	1	1,079	11,171
Medical	0	5	184
Industrial	36	2,600	7,675
TOTAL	112	7,104	25,993

Figure 17: Neuromorphic revenue breakdown per markets. Each market itself presumably requires different types of classification tasks such as digit recognition or speech recognition. (Yole Development, 2019. Neuromorphic Sensing and Computing 2019; Market and Technology Report). Note, that the circles go from 2024, the latest on the inside to 2034, the latest on the outside.

As can be seen in **Figure 17**, the first wave from 2024 onwards will be driven mainly by the mobile sector, with the industrial sector in second place. Please note that this distribution should be put into perspective because the market will still be extremely small and the sales volume very low. Around 2029, these two segments should be leading the way, with a substantial increase in automotive. Finally, around 2034, which should be the date of maturity of the neuromorphic market, the automotive sector will be in first position and the industrial sector in second position and should surpass the mobile sector.

The applications in the three fields are extremely vast, hence it is not possible to go into too much detail here. Nevertheless, a few remarks can be made.

To date, the automotive market is mainly based on sensors towards autonomous vehicles. The applications for the (production) industry are mainly based on the new robotics revolution which also means automatization and an increased need for “independently operating” machines. The continuous improvement of the automation of production lines and logistics also represents an opportunity sector for task classifications. The mobile and consumer markets are often lumped together. However, if we separate the two, we can see the overwhelming dominance of the mobile market. In this area, classification tasks clearly have a special place. In terms of volume, this is where the biggest business opportunities lie.

Segmentation data can be very interesting for selecting partnerships and applications to focus on in the future and over time. A few other data can be drawn from which are in line with remarks often made by specialists.

The medical market, for example, which could be expected to generate higher sales volumes, is a niche and will remain so for some time. This field is less open to AI innovations, in particular because of the much stricter legal framework and the risks it arouses. Although extremely interesting applications with great social benefits exist, including in the field of speech recognition (for example, the Parrotron project supported by Google and inspired from the Euphonia project, which is working on speech recognition for people with disabilities like neurodegenerative diseases), the medical sector remains limited and essentially driven by research on imaging.

In any case, the market segmentation and the volume represented by the different segments are elements that should not be neglected when choosing applications and end users.

2) Dominant trends in neuromorphic applications:

The two trends presented here are not the only ones that are stirring up the neuromorphic market, which is really booming. However, they stand out in particular, and although the k-NET project does not aim to address them immediately for the proof-of concept demonstration, it is relevant to mention them briefly (without explaining all the technical ins and outs), particularly as the versatility of the technology may make it possible to imagine different applications in the future.

- **Event-based sensors and cameras:**

Event-based cameras and sensors have critical advantages over conventional cameras and sensors, such as low latency, lower power consumption, high temporal resolution and high dynamic range. Their real-time capability is essential for the artificial intelligence sector such as robotics, autonomous vehicles, IoT surveillance systems, eye-tracking and control systems for augmented reality.

The event-based camera and sensor companies are **mostly European start-ups, with the exception of Samsung and the Chinese company Celepixeli**. European companies include the French companies Prophesee or Insightness and Inivation from Switzerland. Samsung is the major technology company that dominates this sector by far.

Recently, interest in event cameras has exploded. Sony has bought Insightness, the agreements between Sony, Bosch and Intel with Prophesee have led to strong partnerships with Intel, Bosch and Sony, and different sectors are interested as shown by the strong patent activity of Apple, Toyota or Huawei.

k-NET being intrinsically a dynamical computation approach, it does not apply well to sporadic event monitoring, it nevertheless could be included in the neuromorphic signal processing at the backstage of the camera (or the sensor).

- **Memory:**

Emerging memories are another really promising technology area. Emergent memories can emulate synaptic elements in a very compact way, enabling massive parallel computations in a fast and efficient way [38]. Advances in this area are very promising not only in terms of inference capabilities but really enable a move towards on-chip training, one of the revolutions in edge computing and neuromorphic computing. Interest in the use of non-volatile memories on neuromorphic chips has grown very significantly in recent years

Major players are present in this field such as IBM, Samsung or Qualcomm, but one should also keep a close eye on. Another promising start-up in this field is Rain-neuromorphic, mentioned above.

k-NET has the advantage to propose a fading memory approach well suited for computing but less relevant when it comes to long-term memory needs.

3) Focus on the potential of classification tasks with speech recognition:

As we currently plan to choose for the proof-of-concept demonstration of k-NET, vowel recognition as the first classification task it is also important to investigate the specific market potential for speech recognition as well.

Generally, the market for classification tasks is extremely large like the AI market. The main market is by far the image classification market as shown in the **Figure 19.**

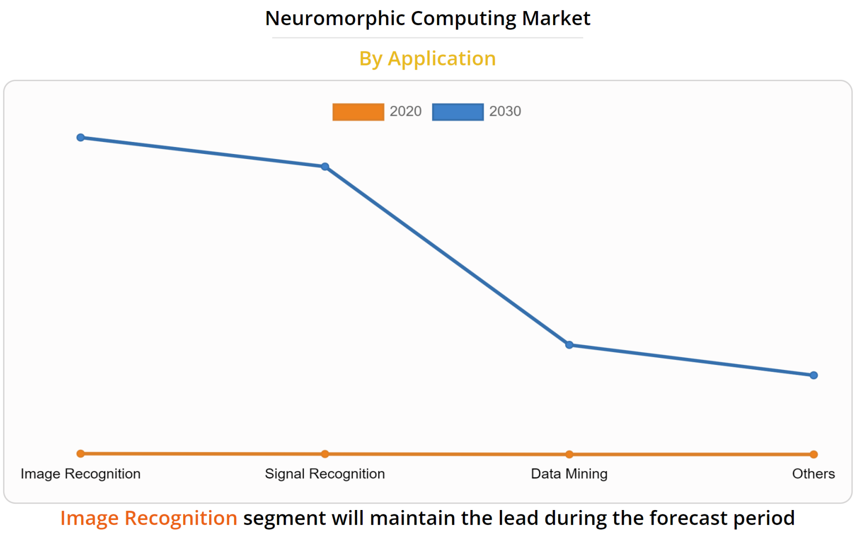


Figure 19: *Development of the neuromorphic market segmentation per classification task between 2020 (orange) and 2030 (blue). One can see that the classification tasks of image and signal recognition will become dominant in the future. With k-NETs potential to perform both of these tasks, there is definitely a number of possibilities to enter the market later on. Figure from Modor Intelligence.*

Thus, here, different task classifications linked with speech recognition will be discussed in more detail. The latter, represents a sub-segment of the AI market dedicated to language analysis. Note, that this also includes conversational robots, machine translation, data extraction, summary creation and text generation, to name only a few examples.

The field of speech recognition mainly exploits deep learning and recurrent and memory networks. This field of AI is, however, a little less mature beyond the fundamental research level than that of image recognition. The complexity of speech recognition stems from context-dependent variants in expression and also from ambiguities in language. However, the adoption of deep learning has recently advanced this field enormously.

The possible applications are vast, but two segments are particularly important. First of all, the IoT and mobile segment. In this sector one finds the whole field of voice assistants, translation software, etc. This is an area that has been widely documented. This is a very well-documented area, now quite structured around the digital giants.

The other most important sector is that linked to marketing and the constitution of exploitable voice data, to which we can add call centers and customer management.

Large start-ups are active in this segment such as Cogito who raised 120M€ and analyses calls in call centers to help online advisers in real time. It is a spin-off of the MIT Media Lab that exploits behavioral science [39].

They leverage IBM Watson APIs dedicated to natural language processing such as Personality Insights, Natural Language Understanding, Tone Analyzer, Document conversion, Twitter Insight and Natural Language Classifier.

The French start-up AlloMedia who raised $12.3M uses speech recognition to extract structured and semi-structured information from customer dialogues in call centers, to feed their CRM databases and improve lead transformation [40]. This is what MonkeyLearn and Dialpad also offer.

- **Cloud/data center for speech recognition:**

The emergence of neuromorphic applications in this area faces the same bottleneck for scaling up as the entire neuromorphic sector (already discussed). k-NET approach can be relevant for this kind of application. This market is nevertheless too mature to be targeted at this stage.

- **Edge market:**

On the contrary, k-NET based neuromorphic computing could take advantage of the edge market trend in speech recognition. With the increasing power of embedded processors in mobiles and other connected objects, there is less and less need to go back and forth to servers in the cloud. There are two possibilities for using the classification of speech in the edge market: the first and the most obvious one is to allow full autonomy of at least some functionalities and not to have to send data to the cloud (used for applications with increased energy efficiency or security among others).

The other possibility is to perform pre-processing tasks. The best-known pre-processing tasks are:

- Data cleansing
- Data editing
- Data reduction
- Data wrangling

Pre-processing allows to significantly improve the datasets and the quality of the final processing, and to increase the security of the data.

Note, as stated in the first part on the physical implementation that a more generic application of k-NET would be the use as a pre-processing chip due to the envisioned versatile use for different classification tasks, its training and inference properties.

- **On-Premises for speech recognition:**

On-premises software refers to software established within the organization's internal system along with the hardware and other infrastructure necessary for the software to function (meaning that the hardware is on-site, and the data comes via a local network). Just like the edge, the objectives can be to enable total autonomy in analysis or operation (this time not at the level of a device but on site). On-premises classification tasks can also simply consist of pre-processing actions as mentioned above for the edge. Although niche uses are conceivable, the use of on-premises technologies are currently mainly of interest in industry and in large logistics centers for example.

On-premises technology has indeed certain shortcomings which mean that it can only be used in certain sectors. The cost of infrastructure is high and so is the cost associated with the software, which is sometimes developed or adapted to a special use-case.

On the other hand, this type of computing is relevant for very large infrastructures that receive a very large flow of data. In the industrial sector, on-premises speech recognition could be used, but only on the margin. A specific but very interesting use in view of the volume of the market could be in call centers.

Once again, it is a question of processing the data in its entirety if the need is only for a fairly simple classification or pre-processing it before sending the data. The objective is to avoid sending sensitive data or heavy and irrelevant datasets to the cloud. Call centers are a huge market and very prone to automation and speech classification.

Many tasks can be automated to reduce staff costs but also to improve security for example (e.g. the speech recognition biometrics solution for call centers from project partner Thales, part of its Trusted digital identity platform) [41].

Beyond automation, it is mainly about the processing of marketing data. In this area, on-premises pre-processing tasks are extremely relevant. The flow of data to be analyzed can be very large and initial on-site processing clearly helps to reduce the mass of data and security and confidentiality (a crucial element from the point of view of compliance with laws and regulations).

- **Examples for speech recognition applications from different neuromorphic players:**

I. INTEL Loihi : In cooperation with Accenture, Intel compared the ability of Loihi to recognise voice commands with that of standard graphics processing units (GPUs). Intel claims that Loihi achieved similar accuracy being up to 1,000 times more energy efficient and responding up to 200 milliseconds faster. Through their neuromorphic community, Mercedes-Benz is exploring how these results could apply to real-world use cases, such as adding new voice interaction commands to vehicles [25].

II. **Tianjin University** developed their Tianjic hybrid chip to separate spatial and temporal processes within the hardware. Researchers processed the voice recognition and detection process with the neuromorphic chip whereas the object recognition & detection applications were done with GPU. They used this solution to control a smart bike. The objective is to benefit from the features of the two technologies [42].

III. Within **HBP, the University of Heidelberg** has developed two native spiking datasets for speech classification and keyword spotting. These datasets are based on the Heidelberg Digits which consist of 10K high-quality audio recordings from zero to nine, and Speech Commands which consist of 24 single word command from 1864 speakers. Combined with the native visual ones, Heidelberg's two audio datasets provide a generic benchmarking tool for neuromorphic community [43].

6.5. General and summary remarks on the market study:

Several elements emerge from the market analysis. The first thing that was not necessarily the most obvious, is that there are many signs that the theoretical potential of neuromorphic computing (which was mostly known by the scientific community) is taking off and becoming a reality in the market. The biggest players, such as IBM or INTEL - and even if they do not have launched their commercial chip yet - are developing more and more application-oriented partnerships, involving players in the segments that will be the most promising in the neuromorphic revolution (automotive, mobile applications, etc.). Start-ups are multiplying, they are raising substantial funds, we are seeing buy-outs and the first ones are launching a real commercialisation, starting with Brainchip and its Akida chip.

The second element is that this burgeoning activity is taking place in the context of a still very fragmented market. There are many activities but they are still on a small scale. The overall amount of investment is increasing but fund-raising remains fairly limited for the electronics market. Most of the funds raised are in the order of 30 million euros, which, as mentioned above, is a very encouraging sign, but shows the immaturity of neuromorphic computing and the fact that it is still seeking its place. The technical versatility of the k-NET concept is interesting from this point of view, making it possible to avoid finding oneself in a dead-end street and carrying out work that will not meet its users.

Nevertheless, some major drivers are emerging that should structure the neuromorphic market. The most promising segments will be mobile, industrial and automotive. The market will, at least initially, be driven by the edge. Event-based and memory are the elements that are attracting the most interest. Image processing will be, as in general for AI, the first sector, but audio processing will be the second point of the task classifications. All these elements will be undoubtedly strong markers.

On the specific subject of the speech recognition classification tasks for the first proof-of concept device based on k-NET, the elements mentioned in the document show the relevance of the choice of this use-case. The most buoyant segments will obviously be concerned and the sales volume will be high enough to hope to attract investors. In particular, the most promising segments that are extremely sensitive to innovation (and already heavily penetrated by AI) are concerned by the most obvious applications. Mobile (and consumer) in the first place, but also call centers and, more broadly, audio marketing processing. These players could largely be the first relays to make the technology evolve towards the market and allow the application domains to be extended.

7. Conclusion and outlook:

The corpus of deliverables 4.1 and 4.2 serves well as a first bridge to connect the theoretical and radical new approach of k-NET with a tangible market reality. The project is low TRL and still at an early stage so the work will inevitably further evolve and change the approach. However, this preliminary work allows us to foresee pathways emerging and may allow the approach to mature in a context that is better known and therefore easier to grasp.

It therefore allows the outline of a coupled development and exploitation strategy. Within the market context summarized in this document, any disruptive approach such as that of k-NET should be benchmarked against existing solution some of which are already commercial products. Given the change in paradigm in the way information is handled in a k-NET device, this benchmarking will need to address the full k-NET methodology including data pre-processing to binary data output. Such a task cannot be performed at once. We therefore are choosing to first prove the feasibility by using a standard benchmarking example such that of vowel recognition. In this stage we will not evaluate the pre-processing and post-processing costs. If successful, the second stage will be to evaluate those costs and identifying the use case that makes them the most relevant for market penetration.

In practical terms, the next steps are now to steer the initial research work already carried out towards the proof of concept as we have defined it here and to be able to validate the first encouraging results for the mentioned specific use-case. On the other hand, the lessons learned from the brief market study should be used to refine the exploitation strategy so that the final end-user workshop can be thought through and prepared in such a way that it can be of great use for the potentially interesting use of the project results beyond this.

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