Deep Learning-Driven Edge-Enabled Serverless Architectures for Animal Emotion Detection

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Animal emotion detection, including elephant emotions, is highly possible, but what the traditional emotion detection approaches highlight is their blatant ignorance of adopting edge-enabled intelligence and serverless-based solutions, both of which are affordable. Treating the emotions of animals increases their productivity, especially among trained elephants when subjected to carrying logs or undertaking gargantuan tasks. However, existing infrastructures are inefficient in handling long-running animal emotion detection-related tasks. This article proposes a deep learning-driven edge-enabled serverless architecture after evaluating several existing animal emotion detection techniques. Additionally, we perform an exploratory study on the cost impact of incorporating serverless-enabled approaches to animal emotion detection architectures. We observed that the proposed edge-enabled serverless architectures saved over 13,000 dollars annually compared to traditional animal emotion detection approaches. In addition, the article provided a few research directions to develop novel edge-enabled serverless architectures that boost socio-economic situations while avoiding human-animal conflicts.

Povzetek: Predlagan je sistem za zaznavanje čustev živali na osnovi globokega učenja. Model povečuje učinkovitost analize, zmanjšuje stroške in izboljšuje interakcije človek-žival.

1 Introduction

Many animals, the vital sources of enabling a sustainable natural environment, have been integral companions of humans for years to share emotions. Emotions are, in general, considered distinct physiological responses that trigger activation signals from various sources, such as the face, body movements, and eye/ear/tail directions.

The emotional traits of animals can bring forth immense psychological relations, leading to research directions that relate to natural survival ethos. For instance, the postures of animals, while proactively reacting to natural disasters, prevent major losses in lives, especially in rural areas. Researchers have observed an anomaly in the behavior of toads and birds before earthquakes. Also, monitoring the emotions of farm animals such as pigs, cows, and sheep, has increased productivity in yielding milk or food products. These prior experiences have led researchers to correlate the emotions of animals with productivity measures.

In fact, emotions in animals have driven researchers to pursue research in various dimensions. For instance, i) almost many veterinary researchers have reckoned in summing up the animal health behaviors to study human health issues – i.e., the treatment of rare psychological human diseases has been analogously studied using laboratory animals [48]; ii) researchers have focused on monitoring the emotions of trained wild animals, such as elephants, that are involved in carrying logs or erecting poles in remote locations or forests to increase the much-awaited human-animal bonds [53].

Although many animals exhibit emotion, there are several challenges in identifying and classifying them appropriately. The most notable challenges are listed as follows:

1. Varying Degree of Emotions – Animals have differing degrees of emotions. They reveal sadness and happiness in varying degrees when compared to most human beings around the globe [5].

2. Differing Emotions among Animals – The empathy revealed in rats is different from the empathy exhibited by elephants. Researchers have recorded moments that portray the differences among animals. For instance, elephants mourn in the worst situations, such as the deaths of mahouts. On the contrary, dogs comfort their masters while strange incidents happen at home.

3. Varying Emotional Features – The features associated with emotions are unique to animals. Hence, developing one robust AI-assisted solution or framework that suits detecting the emotions of all animals is a challenge.

4. Algorithm Designs – Tens of thousands of learning algorithms exist on the market to detect emotions in human faces or mobile-assisted applications [35]. However, for developers, there are not many learning algorithms that could accurately capture the emotions of animals with limited computational or communication requirements.

There have been efforts in the past to study the emotions of animals [57], [68] – for instance, researchers have developed sensor-enabled systems and AI-assisted solutions to detect the emotions of animals. However, it is crucial to understand the pros and cons of these solutions so that new approaches can be designed or developed.

This article examines the existing emotion intelligence methods used by researchers to detect animal emtions. The article highlights the importance of incorporating edge-enabled and serverless-oriented solutions when designing animal emotion detection frameworks or architectures. The article delves into the importance of integrating serverless approaches into architectures by examining the costs associated with using computational resources and memory components for animal emotion detection. Additionally, it throws light on future novel research directions and approaches to animal emotion detection frameworks. The article contributes to classifying animal emotion detection-related works and delivers a taxonomy of animal emotion-related research works.

The rest of this article is described as follows: Section 2 provides a taxonomy of emotion detection approaches in animals; Section 3 expresses the necessity of edge nodes and edge-enabled serverless-based emotion detection frameworks with suitable cost-based exploratory illustrations; Section 4 examines a few possible research directions that a few computational researchers could undertake shortly; and Section 5 provides a few conclusions of the article.

2 Animal emotion detection – A taxonomy

Traditionally, animal emotions were manually detected. For instance, mahouts had to keenly observe the elephants' movements, facial expressions, and sound characteristics before performing actions. In recent years, the manual approach has been replaced with IoT-assisted solutions or AI-based intelligent solutions [75].

This section explains two broad classifications of animal emotion detection mechanisms – Invasive and Non-invasive methods. Before delving into these methods, we have emphasized the difference between animal and human emotions. Additionally, we have listed animals that are often utilized in the state-of-the-art literature to detect emotions in various contexts.

2.1 Human emotions vs. animal emotions

Often, humans deliver emotions using multiple modes of linguistic communication, such as texts or vocals, apart from facial/body expressions or movements. The emotional states of humans have been widely discussed in the past by several researchers. Notably, [64] have developed emotion-oriented facial datasets for the Indian community. Similarly, facial emotion datasets have been developed in the past to be applied in several applications such as driver assistance, fraud detection, culprit detection, and so forth.

In the past, the majority of researchers classified human emotions into six categories. According to [22], human emotions are classified as: i) happiness, ii) sadness, iii) fear, iv) disgust, v) anger, and vi) surprise. However, recently, a few authors [18] have observed a few more unique emotional states in humans. Accordingly, human emotions are represented in 27 different states, such as admiration, adoration, aesthetic appreciation, amusement, anger, anxiety, awe, awkwardness, boredom, calmness, confusion, craving, disgust, empathic pain, entrancement, excitement, fear, horror, interest, joy, nostalgia, relief, romance, sadness, satisfaction, sexual desire, and surprise [18].

Pythagoras and Charles Darwin mentioned that the emotions of animals are equivalent to human emotions [5]. But many other researchers have recently expressed that the emotions of humans are quite deeply intertwinkled in most cases when compared to animals – i.e., the emotions of humans have a mixed expression in some situations that the animals could hardly express. Hence, excerpts conclude that animal emotions differ from human emotions.

In [55], the authors have classified the core emotions of animals into seven categories: seeking, fear, rage, lust, care, panic, and play. These emotions differ depending on the type of animal. For instance, authors of [51] have explored the emotions of elephants in detail; the authors of [42] have translated human emotion traits to study the emotions of animals, with a specific focus on handling conceptual emotions.

In general, elephants reveal emotions in several situations. The most commonly observed incidents in which elephants showcase emotions are listed below: a) Joy during birth – i.e., elephants trumpet and run around each other to express joy at birth; b) Grief during death – i.e., elephants mourn if death occurs among loved ones. During grief situations, elephants reiterate the incidents due to their long memory power. Elephants exhibit certain characteristics that are exceptional to many other animals; c) Anger Emotion – elephants act angrily in several situations, especially when their habitats are occupied by humans. Similarly, they express angry emotions when mahouts urge them to do larger tasks without sufficient food or enough rest. Typically, the spread ears, V-ear, and distracted working style of elephants indicate a sign of threatening people or environments [37]; and, d) Empathy Emotion – elephants also exhibit empathy on three major occasions: i) consoling people or other elephants during any death occurrences, ii)

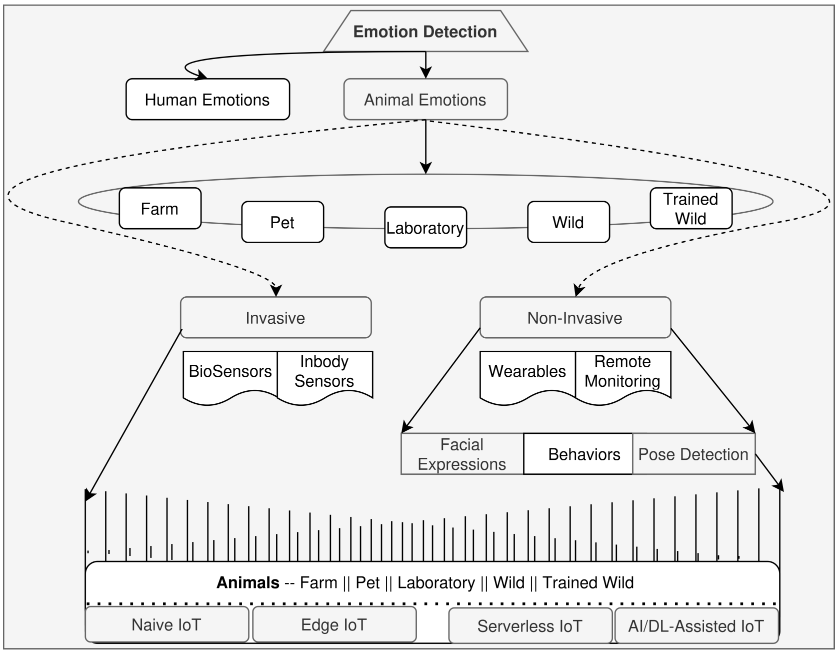

Figure 1: Emotion detection of animals – A taxonomy

defending or protecting young elephants from other predators, and iii) stopping fights, especially when their loved ones are forced to fight each other during unavoidable circumstances.

2.2 Animals involved

Animals involved in observing emotions differ based on the location where they are monitored. Accordingly, they are classified as follows:

1. Farm animals – Farm animals, such as dairy cows, pigs, hens, horses, and so forth, are animals utilized for agricultural purposes such as yielding milk, laying eggs, and providing nutrients. Understanding the emotions of these farm animals and providing better shelter and food can increase the economic capabilities of farmers. It can indirectly increase the financial position of the livestock sector of a nation. In the past, the emotions of dairy cows have been observed in pastures [4, 51]; pigs have been monitored in farms [13, 51]; and, the emotions of sheep have been assessed in farms [45].

2. Pet animals – Pet animals are often utilized by humans to provide a better companion in their lives. The utilization of pet animals such as cats and dogs has increased in multitudes in recent years owing to the loneliness of human inhabitants that they experienced during the COVID-19 era. It is manifested that the productivity of working professionals has increased in multitudes due to the association of pet animals.

3. Laboratory Animals – Laboratory animals are involved in studying the relevant features of humans or their health conditions. The most commonly utilized animals for laboratory-based study purposes are rats and mammals. Learning the emotions of these animals before dissecting them is considered a crucial task for several veterinarians or animal researchers [1].

   In some situations, animals are experimented on in test rooms rather than in laboratories. This is a specific location where emotions are experimented with using sophisticated measurement devices or sensor units. However, the test rooms are not utilized for students or for grading them. For instance, a few pigs have been monitored by researchers in a test room consisting of four positioned cameras associated with computer vision image analyzing systems to study their behavior [68]; also, the emotions of dogs have been evaluated in a room by monitoring their facial expressions and providing rewards to them [9].

4. Wild Animals – Wild animals such as elephants [65] [37], lions, tigers, or so forth that live in forests, such as sparsely dense forests or heavily dense forests, might expose varying degrees of emotion. For instance, elephants' vocalization with varying degrees of emotions has been recorded in forests to capture the wild behavior of elephants [70], [76], and [16]. The purpose of characterizing and learning such emotions is to assess the patterns of invading wild elephants or to save tribal communities from possible elephant attacks.

   In [58], authors have studied the characteristics of sheep when they wandered in a wild forest. This exercise has been carried out to observe the diversity of data sources – wild vs. domestic impacts.

5. Trained Wild Animals – A few wild animals are trained to undertake gargantuan tasks such as carrying logs or showcasing performances in the circus arena. Wild animals performing in circus arenas, such as elephants, tigers, and lions, express emotions considering the trainers' reactions or audiences' appreciation levels.

2.3 Emotion-related features

The emotions of animals are exhibited in animals through specific features. The core features that are instrumental in identifying the emotions of animals are listed as follows:

1. *Pig Emotion Identification Features* – The emotions of pigs are evaluated based on the angle of their ears, snout ratios, and eye movements. If pigs exhibit aggression, ears move forward with a minimal snout ratio; similarly, their eyes are narrowed during retreats [13].

2. *Cow Emotion Identification Features* – The emotions of cows are identified based on the movements of their eyes and ears. If they are excited, the ears are wide open and the eye positions are broadened.

3. *Elephant Emotion Identification Features* – Elephants are considered the largest land mammal on the planet, having the largest brain that weighs up to 5.5 kg. It has a huge physical structure of 3 to 4 meters tall and weighs from 2 to 7 tons. The trunks have over 1 million muscles to undertake several gargantuan tasks, such as carrying logs or removing trees. The trunk portion of the elephant is utilized for several activities, such as defending, breathing, feeding, gathering, smelling, drinking, lifting, and sensing. The brain of elephants is so peculiar due to their enduring long-term memories, which enables them to remember mahouts or emotional incidents even after long years.

   There are two types of elephants: a) *Asian Elephants*: Asian elephants are most commonly found in India, Sri Lanka, and Sumatra. These elephants have twin-domed heads compared to African elephants. They weigh heavier than African elephants in most cases. b) *African Elephants*: African elephants are of two types – bush elephants and forest elephants. The bush elephants are found in several parts of Africa. They are gigantic in nature when compared to the other elephants – i.e., they weigh over 10 tons. On the contrary, the forest elephants are smaller and have rounded ears. The poaching and defending characteristics differ among these two species of African elephants.

4. *Dog Emotion Identification Features* – Several research studies have been carried out to study the emotions of dogs in the past. The crucial features of dogs that impact their emotions are blinking eyes, flattening ears, moving lips, licking noses, and so forth [17].

5. *Horse Emotion Identification Features* – Learning the emotions of horses is based on the evaluation of their eyes, ears, nose, and neck positions. Depending on different emotional traits, horses position their body parts, exhibiting unique emotional features. For instance, i) open eyes, stiffly forward ears, open nostrils, parallel necks, and higher head positions are the indications when horses are alarmed [17, 63]; ii) open eyes, stiffly backward ears, and slightly closed nostrils, are the indications when they are annoyed; iii) open eyes, pointed forward ears (mostly relaxed), and an open mouth with the relaxed neck are specific features when they are curious about pursuing any tasks; iv) shut eyes, pointed sidely ears, relaxed mouth, and parallel neck positions are signs that indicate a relaxed horse; v) rotated ears, dilated nostrils, and raised chin are the indications for revealing pains by horses [59].

2.4 Emotion detection methods

There are two broad categories of emotion detections in animals – i) Invasive and ii) Non-Invasive. In the invasive method, sensors or electronic-based emotion detection devices are either permanently or temporarily inserted into the bodies of animals. These electronic devices can constantly upload measurable properties such as heart rate, temperature, glucocorticoid levels, or physiological changes to the connected cloud or fog-based compute services using wireless communications, including 4G/5G mobile networks for evaluating the emotions. Additionally, animals are utilized to detect natural disasters using invasive techniques [32].

Although this approach has been widely applied in human emotion detection methods, it is not well discussed or practiced in animal research, particularly when considering small-sized animals such as cats, rats, and so forth. However, elephants and similar kinds of endangered species or animals, living in zoos or tourism locations, can adopt invasive methods to detect emotions. The major advantages of adopting invasive methods are twofold: a) Invasive methods rely on more authentic measurements that relate to physiological indications of emotions; and, b) they deliver accurate measurements while observing emotions in animals [51].

In non-invasive methods, emotions are collected using sensors mounted outside the bodies of animals. In fact, detecting emotions such as fear, anger, joy, disgust, neutral, and so forth, using facial expressions has been widely implemented for human datasets in the past [62]. Several methods and algorithms have been designed in the recent past to detect the emotions of human faces belonging to dispersed geographical regions [43] [14]. Also, researchers have captured the relationships between facial expressions and emotions [71].

As similar to identifying human emotions, classifying emotions from the facial expressions has been practiced by experienced animal researchers [29] [74]. They observed that adopting ICT technologies eases the process of emotion detection due to the inclusion of sophisticated learning algorithms to capture the facial emotion-related features of animals. However, while investigating the existing research, we could observe that these mechanisms have targeted single animals rather than a group of animals while detecting their emotions.

A large sector of researchers worked on creating facial action coding systems (FACS) in animals. Notably, FACS was initially developed in human faces by observing facial muscular movements [23]. Subsequently, the same approach was developed in animals such as dogs, cats [12], and horse. [39] applied the FACS approach to indicate pain points in animals; [73] evaluated the facial expressions of multiple animal species. In [19], authors attempted to label the facial features of animals before collecting their emotions. However, their approach led to reduced learning accuracy due to poor precision in labeling the FACS of animals. In a few research works, researchers have applied deep learning algorithms to detect such facial expressions [40].

Facial expressions of animals are useful to capture and assess the severity of pain in animals. An array of research works is based on the grimace score of the facial expressions of animals. In short, the grimace score is an assessment score that indicates the pain levels of animals by observing their facial muscular movements. For instance, in [47], authors have utilized the grimace scale to detect the severity of emotions due to pain [46]. Similarly, the grimace scale indication has been applied in different varieties of animals such as laboratory animals [67], farm animals [30], and pet animals [24] by a few other researchers to study the impact of pains in different animals – i.e., researchers [45] have extended the concept of grimace scales for sheep and named them as Sheep Pain Facial Expression Scale(SPFES) [45]; similarly, authors of [38] and [10] have developed unique grimace scales for horses and named them as Horse Grimace Scale (HGS).

A few authors studied the relationship between animal behaviors and emotions. They monitored the behavior of multiple types of animals by assessing the behavior indicators [61]. For instance, the authors of [21] have developed a cow emotion estimation framework considering the valence of the affective states of cow's behaviors; the authors of [33] have implemented a few behavior indicators of pigs based on the wagging of their tails; the authors of [20] have classified the emotions of horses after collecting their behavior traits; authors have explored and affirmed the repetitive pattern of horse movements that reduces their stress level [3]. Also, in [56], the authors have developed a monitoring framework that keeps track of the behavioral states of animals.

Apart from farm or pet animals, we collected research works that focused on the behavioral study of elephants. Notably, researchers [66] and [8] have studied the behavior patterns of elephants using vocalization and vocal expressions.

2.4.1 Using pose detection

Identifying the poses of animals and relating them to their core emotions is another aspect of detecting emotions in animals. The body posture and movements of animals convey emotional indices. The correlations between pose and emotions can be studied using modern learning algorithms, including deep learning algorithms. Such studies relating to animal emotions based on pose estimations can be instrumental in minimizing pain in animals.

For instance, in [77], the authors have developed a pose estimation system for dogs to assuage their pains. In the recent past, authors have developed a DeepLabCut framework [63] that relates the emotions of dogs, such as happiness, fear, and anger, to their corresponding poses. They have detected a few abnormalities in horses' poses while considering their movement patterns.

There are a few tools that estimate the poses of animals and relate them to their emotional states. Notably, the DeepLabCut tool [44, 26] and the LEAP tool [57] have been widely utilized among researchers and practitioners to capture the emotions of animals using deep learning algorithms. The DeepLabCut framework has also been utilized to generate emotion indicators from several cross-species of animals based on learned poses [50].

The summary of the existing works point out that most of the works have not applied specific cost-efficient solutions to detect animal emotions in real-time. Table 2.4 highlights the animal emotion detection systems that differentiate the non-inclusion of cloud-based systems or IoT-enabled approaches.

In the table, we have defined N as NIL, NS as Not Scalable, OFF as offline, ON as online, $S-Exp$ as standalone experimental setup, $S-GPU$ as standalone experimental setup involving NVIDIA or similar GPU-based machines, $Cloud$ as cloud-based solution, and $S-Drone$ as standalone experimental setup based on drones. The last metric denotes the cost efficiency in a scale ranking between 1 to 5 where 1 corresponds to the cost-efficient solution.

The idea is to point out that serverless-based edge-enabled solution could be a better approach for detecting animal emotions that surpass a long time internal.

3 Edge-enabled serverless architectures for animal emotion detection

With the alarming rise in interest in establishing human-animal bonds and preventing animal attacks, robust technologies are required to detect the emotions of animals.

Table 1: Animal emotion detection and allied techniques – a comparative study

Article	Methods and Procedures	–Computing | Scalable | Offline/Online | Cost Scale
[4]	Manual analysis	N | NS | OFF | 3
[51]	YOLO and FasterRCNN for detecting cow emotions	S-GPU | NS | OFF | 4
[1]	Pre-trained CNN to study post surgical impacts of mouse	S-Exp | NS | OFF | 4
[10]	Horse pain detection using machine learning	S-Exp | NS | ON | 2
[17]	Facial emotion detection of horses	S-Exp | NS | OFF | 4
[26]	Dog's emotion detection using neural network	S-Exp | NS | OFF | 4
[29]	Identify emotions in monkeys	S-GPU | NS | OFF | 4
[33]	Tail posture identification in pigs	S-Drone | NS | ON | 4
[38]	Pain in horses using CNN	S-Exp | NS | OFF | 4
[58]	Disease prediction using CNN	S-Exp | NS | OFF | 4
[70]	IoT-based elephant acoustic study using Neural network	Cloud | S | ON | 2
[74]	RetinaNet face posture identification	S-GPU | NS | OFF | 4
[77]	YOLO and LSTM-based pain detection in dogs	S-Exp | NS | OFF | 4
[34]	CNN-based animal face detection	S-GPU | NS | OFF | 4

This section discusses the edge-enabled serverless architectures and frameworks that adopt an efficient animal emotion detection mechanism.

Towards this end, at first, we cover the special features of architectures that are crucial to detecting animal emotions; next, we describe the possible software/hardware components and associated algorithms that improve the goals of identifying the emotions of animals; and, at last, a few metrics that drive the objectives of architectures are discussed.

3.1 Animal emotion detection architectures

In the past, specialized trainers detected animals' emotions. They applied skilled tricks to improve the productivity of the animals' assigned tasks. For instance, vocalizations such as growls, barks, or body postures such as wagging tails of dogs, are read by people raising animals. However, observing emotions and classifying the affective states of animals using the manual approach can lead to human bias [49]. There have been efforts in the past to develop mechanisms that offer unbiased assessments. However, the works are under-researched to date [36].

This section elaborates on the applicability of IoT-enabled technologies for studying the emotions of animals. Depending on the deployment options, the animal emotion detection mechanism is classified into four types: i) Naive IoT, ii) Edge-enabled IoT, iii) Serverless IoT, and iv) AI-Assisted IoT (see Figure 2). Additionally, the section highlights the importance of involving deep learning-driven edge-enabled serverless architecture to enhance the accuracy and cost efficiencies.

3.1.1 Naive IoT – Type-I

Exploring the emotions of animals utilizes sensor-enabled networks that transport sensed data using communication protocols such as WiFi, 4G/5G, or Long Range WAN (LoRAWAN). The WiFi communication protocol provides a higher bandwidth to transfer sensor data from a camera. This protocol is suitable in locations such as zoos, temples, and work sites, where the emotions of animals need to be monitored. 4G/5G networks are mobile cellular networks based on 4G/5G communication protocols that offer a high-speed network to carry animal images or video streams in a wireless medium. However, this protocol is not suitable for carrying sensory information for long distances. On the contrary, LoRAWAN is a wide area network that can transfer sensory information that reaches around 10 KMs between sensors and services. The drawback of utilizing the LoRaWAN protocol in emotion detection architectures is its limitation in transferring a huge volume of data to sense the emotions of animals.

In the Naive-IoT system, sensors such as camera sensors collect animal images or frames and stream data to cloud services through gateways that are connected using communication protocols such as WiFi or 4G/5G networks. The cloud services process these animal videos in cloud environments after sufficient data processing mechanisms, including data filtering, augmentation, and so forth. Additionally, the cloud services host learning algorithms or AI-assisted services to detect the emotions of animals, such as anger, grief, happiness, joy, and so forth.

For instance, in [54], the authors have developed an IoT-enabled electronic board using sensors that were mounted on the ears of pigs to observe their activities; [41] have developed an accelerator-based solution to collect the behavioral changes of horses by designing a few affective states; [69] have studied the emotions of animals by transforming learning algorithms on smartwatches; and so forth. Similarly, [52] have surveyed the sensor-based emotion monitoring approaches for farm animals, which limit the scope of research to a subset of animals. In Figure 2, we could observe that the Type-I architecture has direct communication of sensors to cloud environments.

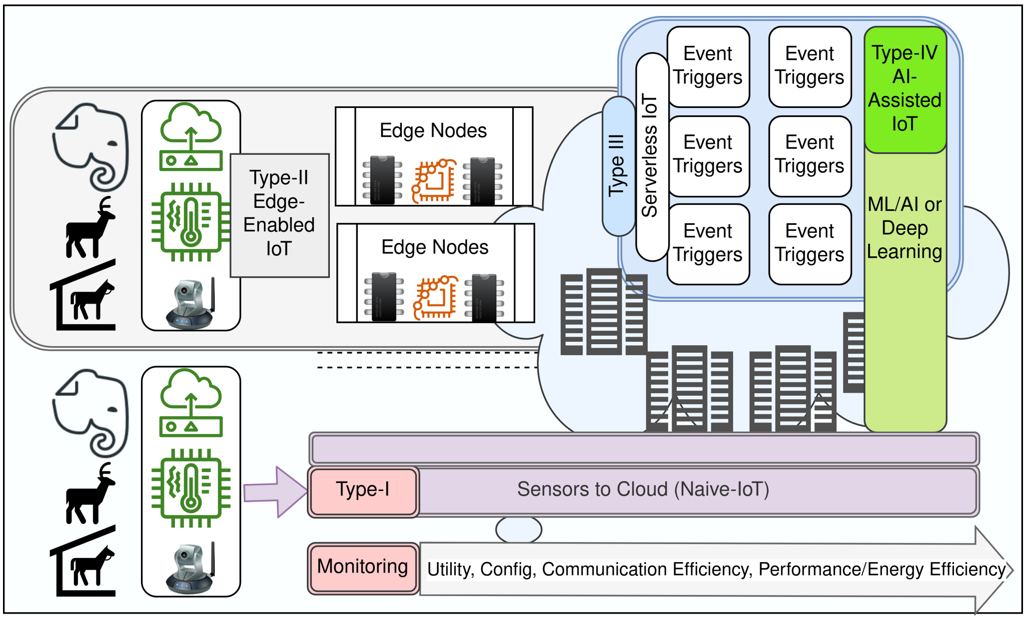

Figure 2: Animal emotion detection architectures – Type-I, II, III, and IV

3.1.2 Edge-enabled IoT – Type-II

Rather than streaming animal videos from their exact locations, such as the zoo or circus arena to the cloud environments, it is better to transfer the important features of animals' emotions to edge nodes. This enables us to minimize the network bandwidth and privacy of streaming sites. For instance, to observe the emotions of elephants, while learning their emotions, it is sufficient to submit features such as ear positions, mouth angle, and so forth, to cloud services based on animal emotion detection services. Most of the video processing and parsing of facial features or emotional traits could be carried out on edge devices that are mounted by decent processing elements. The most notable edge devices that are utilized for processing video frames nearer to the sensor nodes are Raspberry Pi nodes, mobile phones, low computational servers, laptops, Jetson Nano devices, and so forth. The type-II architecture model of Figure 2 represents the sensors connected to clouds through edge nodes. A few researchers have developed frameworks with multi-sensor devices, including cameras, to detect the emotions of elephants on smartphone devices based on GPS communications [70]. However, this work is not assisted by modern communication protocols or edge computing services to efficiently utilize the power of edge-enabled IoT systems.

In fact, edge computing nodes suffer from memory and computation-related resource limitations. They could not handle memory-expensive deep learning tasks such as ResNet50.

3.1.3 Serverless IoT – Type-III

Most IoT-enabled applications or pure edge-enabled solutions continuously power the associated cloud services. This approach of utilizing edge and cloud computing nodes for processing animals' emotions has three major disadvantages:

1. *Energy Inefficiency* – Cloud services are unnecessarily underutilized, even if there is no data to process them. For instance, the videos of animals are not captured throughout the day/year to study the emotional variations over time in the zoo. The emotions could be programmatically observed only for a few minutes, especially while feeding, playing, or so forth. In such situations, cloud servers could be switched "OFF" to efficiently handle the energy consumption of these applications. Also, in locations where renewable energy sources are available, it is sufficient to utilize renewable energy sources to power "ON" the devices.

2. *Cost Inefficiency* – In cloud environments, compute instances and their allied resources for applications are continually utilized. If we need to detect the patterns of emotions in animals over months or years in a zoo/circus, the cloud resources are always utilized, although the necessity of resources is limited. This indirectly increases the costs of such emotion detection-based applications for users.

3. *Carbon Inefficiency* – When animal emotion-related applications are executed on clouds, they heat the cloud resources. Obviously, energy consumption due to powering "ON" the machines and cooling them due to overutilization the risk of carbon emissions in data centers or supercomputers. These carbon emissions, therefore, could be controlled for the benefit of society if the applications are programmed elegantly.

Table 2: Deep learning algorithm-based animal emotion detection

Reference	Animal	Algorithm	Approach	Location
[59]	Horses	Object Detection NN and YOLO	Facial Keypoint Action Movement Detection	Horse Staple
[2]	Horses	LSTM concatenated binary classifier	Facial Keypoint Action Movement Detection	Horse Staple
[51]	Cows, Pigs	FasterRCNN YOLOv3 YOLOv4	Emotion Classification using different Algorithms	Pasture
[27]	Dogs	Pretrained AlexNet with FC Layers	Emotion Pretraining	-
[26]	Dogs	DeepLabCut	Landmark points and posture detection (Ear, Hair, Mouth, and so forth)	-
[1]	Mice	ResNet50	Emotions post surgical	Laboratory
[17]	Horses	FasterRCNN VGG16 ResNet50v2 Xception	Comparison of algorithms based on head positions	Farm land
[7]	Dogs	ResNet Supervised	Classify emotions based on anticipation or frustration	Home
[58]	Sheep	YOLO SSDMobileNet	Sheep face detection	Farm land
[38]	Horses	3-layered CNN	Facial feature classification based on Grimmascale	Farm land
[10]	Horses	InceptionV3 VGG+LSTM	Pain detection with temporal features	Farm land
[60]	Horses	Encoder-Decoder	Equine pain classification	Farm land

A serverless-enabled cloud implementation model improves energy efficiency, cost efficiency, and carbon efficiency. It is a cloud execution model where servers are not powered “ON“ throughout the execution of applications. Only if sensor data is triggered using edge-enabled devices, the servers are powered “ON“ and the states of the applications are modified.

For instance, the emotions of animals are assessed based on the qualified input data captured and transferred to cloud servers. There exist a few platforms that enable serverless-assisted IoT solutions. For instance, AWS offers Lambda services. The Lambda services enable execution of functions based on triggers obtained from IoT-enabled sensors.

3.1.4 AI-assisted IoT solutions – Type-IV

Providing AI-based solutions is crucial to accurately detecting the emotions of animals. AI-based algorithms, in general, are classified into supervised, unsupervised, and reinforcement learning algorithms [6]. They are applied in various domains, such as the financial sector, agricultural sector, cognitive sector [15], and so forth. Supervised learning algorithms are further classified based on machine learning approaches and deep learning approaches.

There are several classical machine learning algorithms such as Support Vector Machines [39], Random Forests, K-Nearest Neighbor, Rule-based, Naive Bayes, Principal Component Analysis, and so forth, that could be adopted for identifying the emotions of animals from varied input sources such as texts, video, or audio sources. Notably, authors have utilized the vocalization features of elephants [70] to detect the state of mind using SVM classifiers in four different categories: roar, rumble, trumpet, and cry.

Apart from a few classical ML algorithms, there exist a few deep learning algorithms such as the You Only Look Once (YOLO) algorithm, Convolutional Neural Networks (CNNs), Residual Net (ResNET) models, Reinforcement Neural Networks (RNN), and so forth for detecting animal emotions.

For instance, in the recent past, the authors of [31] have assessed the pain in horses [2] and donkeys by detecting the facial keypoints; the authors of [25] have applied the ResNet50 algorithm to detect pain in cats; researchers of [45] have utilized computer vision approaches to detect pain in animals; in [28], the authors have implemented an IoT-enabled solution to establish an intelligent ecosystem for tracking the health of diary farm animals in real time.

Similarly, authors of [72] have implemented a Faster R-CNN deep learning algorithm to classify animal emotions; a few authors have observed the emotions of farm animals using pre-trained Deep CNN models when projected with wolf sound and images [51]; a few researchers, [27], have developed a simple pre-trained AlexNet deep learning model to classify the affective states, namely, smiling, growling, and sleeping states of dogs; a few other researchers [1] have developed an emotion detection model based on neural networks supported by binary classifiers that detected mice’s post-anesthetic surgical emotions based on facial expressions; a few researchers [17] have studied the facial expressions of horses using CNNs; a few authors have worked on the application of deep learning algorithms for improving the emotion intelligence of dogs [7] and cats [25]; and, so forth.

Additionally, authors have utilized a pre-trained ResNet-based deep learning model to classify the emotions of dogs as anticipation or frustration [7]; authors [58] have developed temporal features as input to detect the emotions of sheep using multi-step CNN models; in [38], researchers have implemented 3-layered CNN-based deep learning models to recognize pain in horses using grimace scales; similarly, several researchers have applied temporal features in deep learning algorithms, including encoder-decoder-based self supervised deep learning algorithms [10] [11] [60], to detect the emotions of animals.

Based on the most commonly utilized deep learning algorithms, we classified and tabulated them in Table 2. Observations reveal a lack of extensive research on the resource or cost efficiency of learning methods in animal emotion detection.

Interestingly, by integrating these potential deep learning algorithms into edge-enabled serverless frameworks, we can quickly, accurately, and efficiently detect animal emotions when sensors such as cameras trigger sensor data in real-time.

3.2 Architecture evaluation metrics

The animal emotion detection architectures such as Naive IoT, Edge-enabled IoT, Serverless IoT, or AI-Assisted IoT have to be monitored and evaluated. We identified a set of performance metrics that could be utilized in the architectures. The description of these metrics is explained below:

Device utility The device utility is a measure of the total utilization of cloud or sensor-based resources among the available utilization times. In serverless environments, the resources are utilized only when there is a trigger from associated sensors – i.e., the utilization depends on the nature of applications, serverless platforms, and resource providers' serviceability.

Configurational easiness Configuring a serverless-enabled IoT platform can lead to difficulties for some users. For instance, a few serverless platforms utilize sophisticated user interfaces or ease in setting up automatic configurations, whereas, others do not. Hence, depending on the ease of setting up the configurations, we classify the architectures.

Multi-communication support An animal emotion detection architecture is limited to supporting all communication protocols. Some architectures enable various communication protocols such as, WiFi, Bluetooth, 4G/5G, and so forth. However, the cost of the system increases if these devices operate with different communication protocols. For ease, based on the utility of the application, several IoT-enabled emotion detection architectures are designed using WiFi, 4G/5G, or Bluetooth. This metric ensures the ability of the device to install it on any different locations/platforms.

Prediction accuracy The emotion detection of elephants or animals in farms or in the wild involves learning algorithms, including deep learning algorithms such as CNNs, LSTM, or SVM. While classifying emotions depending on the environmental inputs, prediction accuracy is one crucial metric that needs to be maximized. If not, false positives drive the system with wrong decisions. Developing an emotion detection system that offers more accurate decisions is a time-consuming task, as it depends on the quality of the learning algorithms and the learning parameters of the algorithms.

Energy or hardware-related metrics The performance of applications is a step toward improving the implementation strategies and the writing style of applications. In an edge-enabled elephant emotion detection system, developers could implement algorithms, including learning algorithms, in several approaches:

1. *Lightweight Implementation using Containers* – container-based implementations offer lightweight solutions that self-contain all relevant packages to execute emotion detection applications. It is an OS-level virtualization approach in which algorithmic instances are offloaded to multiple servers depending on the load balancing requirements or other performance concerns of the execution environments.

2. *Security-conscious Implementation Approach* – Applications could be developed considering the security features of the programming models. Increasing the security-based software components in emotion-related detection algorithms can reduce the performance of applications.

3. *Execution Time Improvements* – Improving the execution time of learning algorithms, including deep learning-based emotion detection algorithms, requires the application developer to have algorithmic excellence and coding skillsets. Developing algorithms considering the nature of input data and avoiding unnecessary allocation of variables could improve the execution time of emotion detection applications.

4. *Energy or Carbon-conscious Developments* – Metrics that improve the energy efficiency of applications or carbon emissions are predominantly practiced in long-running applications. For instance, edge-enabled emotion detection applications involve battery-operated or renewable energy sources for powering edge or sensor nodes. The entire ecosystem should consciously deliver most of the executions to such renewable-powered resources while learning emotions or inferencing emotion-related patterns. In this way, carbon emissions are reduced in such long-running applications, especially when training phases are carried out on edge-enabled devices.

Figure 2 illustrates the different types of animal emotion detection architectures depending on the deployment options – i.e., whether they involve edge-based solutions, serverless execution models, or naive IoT-enabled approaches.

3.3 DL-driven edge-enabled serverless architecture – an exploratory study

Among the four types of animal emotion detection architectures, the Type-IV architecture that combines deep learning, IoT, edge computing, and serverless execution models is considered to be more efficient in terms of cost and resource utilization.

Table 3: Cost exploration for AWS services in naive-IoT architectures

AWS Services	Name of the Service	Dollars per hour	Year-wise
Compute Instances	t4g.micro	0.0104	91.104
	m5.large	0.096	840.96
	t2.micro	0.0116	101.616
	g4dn.12xlarge instances (4 GPUs - 96vCPUs)	5.47	47917.2
Associated Storage	SSD-32GB	2.56	30.72
	IOPS-SSD-32GB	4	48
Kinesis Data firehose	1TB-streams	29.7	356.4
AWS S3	100GB storage	2.3	27.6
		Total (10 instances)	**12556.8**

Table 4: Comparison of types of animal emotion detection architectures

Architecture	Scalable	Latency	Cost Efficiency	Security	Accuracy	Utility	Easiness
Manual	Poor	Depends on availability	Poor	High	Depends on Evaluator	NA	NA
Type-I	Medium	High	Poor	Poor	Depends on Application	Poor	Poor
Type-II	High	Medium	Medium	High	Depends on Application	Medium	Poor
Type-III	High	Low	High	High	Depends on Application	High	High
Type-IV	High	Low	High	High	Depends on AI	High	Medium

3.3.1 Process involved

The following steps outline the process of incorporating deep learning algorithms into edge-enabled serverless frameworks within the Amazon AWS ecosystem:

1. Initially, camera sensors stream videos to nearby edge nodes for evaluating the animals interested in detecting the emotions. For instance, an elephant emotion detection system captures frames belonging to elephants and omits the other animals.

2. Next, edge-enabled services connect to AWS S3 buckets to trigger the required DL algorithm, such as YOLO, CNN, RESNET, or so forth, using S3 event notification options. The S3 buckets include code snippets and scripts to start executing EC2 instances based on AWS Lambda functions.

3. Accordingly, the corresponding DL algorithm is executed along with the past state information and data modules on EC2 compute instances for a specified time interval. The EC2 service requests are activated through simple queue services of AWS.

4. Finally, once the modeling and prediction tasks are handled, the state of the application is saved in the S3 bucket for future executions. It could be noticed that the EC2 instances remain inactive throughout the animal emotion detection processes, particularly when they are installed in forest or zoo locations. This drastically reduces the computational costs involved in the execution. Additionally, a few lightweight deep learning algorithms, such as TinyYOLO, could be deployed for faster and more resource-efficient learning or inferences.

3.3.2 Cost-efficiency

To illustrate the cost efficiency of Type-IV architecture – specifically, DL-driven edge-enabled serverless architecture, we have considered an AWS platform consisting of 10 Elastic Compute Cloud (EC2) instances, including GPU instances, to execute parallel deep learning models; AWS Lambda and AWS S3 services have been considered to establish serverless implementations. Also, we have assumed that the architecture included cameras and edge devices such as Raspberry Pi nodes that are dedicatedly available for evaluating the costs involved in the animal emotion detection. In the study, only recurring costs involved in the operations were studied, assuming the animal emotion detection has to be evaluated throughout an year.

The key findings are listed below:

1. The manual approach to detecting animal emotions is not a scalable or accurate solution as it is dependent on the skillset of evaluators;

2. The Type-I architecture utilized cameras to stream animal videos directly to cloud-based services. In this approach, at least cloud instances have to be active throughout the execution of services. As an exploratory study, we considered ten `m5.large` instances from the US East (N. Virginia) region to evaluate the animal emotions. Accordingly, the cost of the EC2 instances was estimated – i.e., it reached around $101.616 per year. Additionally, the architecture required high performance storage units to quickly re-

spond to the requests for animal emotion detections. Hence, Solid State Drives (SSDs) or I/O Operations Per Second (IOPS) storage units have to be invoked. Also, we need to process streaming data on the cloud. To do so, AWS Kinesis Data Firehose have to be plugged in to the detection system;

3. Involving ten `m5.large` instances, 32-GB SSD, 1TB-streaming support, and 100GB S3 service can lead to $12556.8 for a year. Table 3 lists the required cloud services and the recurring cost required per year to operate an animal emotion detection-related application on the cloud using Type-I architecture.

4. The Type-II architecture considered edge-enabled devices to parse videos and perform data-related operations closer to the data sources. This architecture still requires cloud-based compute instances and storage units mentioned in Table 3 to evaluate animal emotions. Although a few computations happen on the edge, the cloud services have to be switched 'ON' throughout the year. However, the network bandwidth of the application is relatively improved when compared to Type-I architecture.

5. Type-III and Type-IV architectures involve serverless IoT solutions. Here, the AWS Lambda service is integrated to the animal emotion detection application. In doing so, EC2 compute instances are utilized only based on the trigger happening from data sources. Assuming that there are 10,000 service requests prompted from sensor sites, there are no charges collected specifically from AWS Lambda services. However, the Type-III architecture requires EC2 instances to update weights and perform inferences.

   If fifteen minutes are required for performing each service request, the recurring costs of Type-III architecture for an entire year will reach only $2676 – i.e., 10,000 times of ten `m5.large` instances along with 100GB storage components. The major difference between Type-III and Type-IV architectures is the inclusion of core deep learning models to perform animal emotion detections. Accordingly, the accuracy of Type-IV architecture increases with almost equivalent costs found in Type-III architectures.

6. Additionally, the four types of architectures are compared in terms of scalability, latency, security, device utility, and ease. Table 4 highlights the importance of AI-assisted architecture using serverless and IoT components to detect animal emotions.

4 Research directions

This section suggests a few research directions that could be adopted based on the existing animal emotion detection strategies. The possible research directions are discussed in three major divisions, as shown in Figure 3.

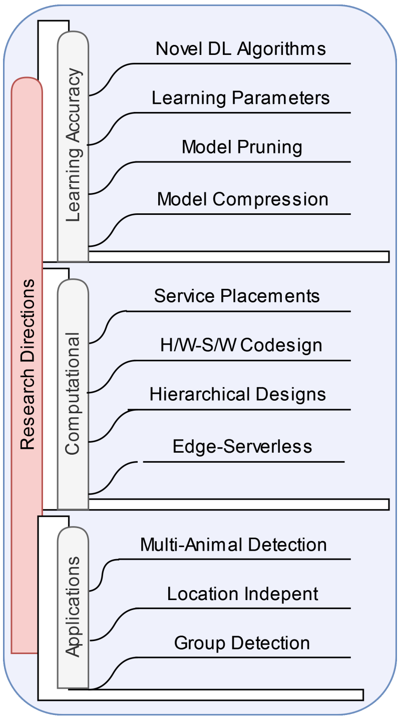

Figure 3: Research Directions in Edge-Enabled Animal Emotion Domain

4.0.1 Improving learning accuracy

Emotion detection using edge-enabled serverless architectures involves learning algorithms such as CNNs or YOLO. The learning accuracy of these algorithms could be increased by applying a few methods, as listed below:

1. the developers could design novel deep learning algorithms that increase the learning accuracy of applications;

2. an automatic tuning of learning hyper-parameters such as learning rate, number of iterations, model optimization methods, and so forth, could be developed. In fact, developing an automatic tuning feature can lead to poor performance efficiencies while detecting animal emotions;

3. an approach to compressing learning models while transferring them to the cloud or edge increases the network bandwidth of the learning system. Unfortunately, researchers avoid them as networks are considerably working well during their experiments with a low volume of data. However, the real situation mandates the necessity of such compressions.

4.0.2 Computational advancements

Although we proposed edge-enabled serverless-oriented architectures for animal emotion detection, there are research directions to improve them i) by choosing where to place the services, such as learning-related services or security-oriented services; ii) by designing tightly coupled hardware-software designs targeting performance metrics such as energy, execution time, or carbon emissions; iii) by developing hierarchical architectures that benefit from the most commonly observed time and space complexities in computing environments; and, iv) by implementing edge-enabled serverless architectures that improve the cost efficiency factors and latency issues of animal emotion detection algorithms.

4.0.3 Applications

Apart from developing technologies and solutions to enhance research in computational and algorithmic design, there are immense research opportunities to observe emotions among a swarm of animals. For instance, identifying animals' emotions from geographically dispersed locations is a challenge. This involves an architectural design of the system, considering sensors and associated communication protocols to transfer intelligence elegantly. Similarly, inferring intelligence based on a group of multi-species animals could spot novel findings.

5 Conclusions

Animal emotion detection research has started with the fresh challenge of detecting emotions. Traditionally, a manual approach to detecting animal emotions had failures and inefficiencies, as pointed out by several practitioners. The recent IoT-enabled animal emotion detection systems have marked an array of performance improvement opportunities. This article explored the recent trends in applying IoT-enabled solutions for animal emotion detection research; it studied the importance of incorporating DL-driven edge-enabled serverless-oriented architectures by exploring the costs involved in computations of architectures; and, it offered a few research directions that threw light on near-future research works. The article would enable the incorporation of novel architectural designs and significantly increase the interest of indigenous animal emotion researchers.

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