OPTIMIZATION OF ENERGY CONSUMPTION IN PRECISION LIVESTOCK FARMING USING IMAGE COMPRESSION ALGORITHMS

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ABSTRACT

Recently, precision livestock farming (PLF) has been developed as a way of improving farm operations by closely monitoring each animal using technology. However, it presents the challenge of how to make the system more efficient in terms of energy consumption. When monitoring animals, pictures and data are recorded 24 hours a day, which can consume a lot of time and memory, making the system slower every time. Due to this, it is important to design an algorithm for the compression of images in PLF, so that animals can be correctly monitored while optimizing energy consumption. There are certain related problems such as using smartphones and sound sensors in PLF, which will be described later in the report. In this work, we proposed a solution for this problem using compression and decompression algorithms such as Nearest Neighbor (lossy) and Huffman coding (lossless), obtaining better results with the last one, as it has a better compression ratio, and uses less time and memory for its execution.

Keywords
Compression algorithms, machine learning, deep learning, precision livestock farming, animal health.

1. INTRODUCTION

Animal products are a fundamental element in most humans' diets; for instance, it is predicted that the worldwide demand for meat will grow 40% in the next 15 years [5]. Due to this, animal health is necessary to ensure that these products for human consumption are produced in the best conditions possible. However, it is very hard, tiring and expensive for farmers to monitor their animals 24 hours a day, so precision livestock farming has been recently developed as a way of monitoring animal health, welfare, environmental impact, production, and reproduction by using technology [6].

Nevertheless, as animals are being monitored all day long, a lot of pictures and data need to be stored, and this can take a lot of time and memory. For this reason, it is important to compress the images that are being taken so that these resources can be efficiently used and distributed, without losing quality and effectiveness of PLF.

1.1. Problem

When using precision livestock farming, animal health is closely monitored to ensure that first rate products are produced. Nonetheless, computers don't have unlimited disc space, which becomes a problem when huge quantities of information are stored. Due to this, compressing images in PLF is fundamental to be able to ensure that animals are correctly supervised at all times, using a system that does not take a lot of time. It is of great importance to solve this problem as farming plays a huge role in the primary sector of the economy, which affects people worldwide.

1.2 Solution

In this work, we used a convolutional neural network to classify animal health, in cattle, in the context of precision livestock farming (PLF). A common problem in PLF is that networking infrastructure is very limited, thus data compression is required.

Due to this, we implemented two different compression and decompression algorithms, the first one, being a lossy image compression algorithm, and the second one a lossless image compression algorithm.

Firstly, the lossy image compression algorithm we chose was image scaling, specifically nearest neighbor, as we consider that it is a very simple algorithm that has a good output after the image is compressed and later decompressed, taking into account that it has losses. Additionally, after checking several examples of compressed image outputs using different algorithms, such as bilinear interpolation, we decided that nearest neighbor algorithm created a clearer image.

On the other hand, the lossless image compression algorithm we chose was Huffman coding, due to the fact that after testing LZ77 and comparing both of these algorithms we realized that Huffman coding was faster and more efficient, and the compression ratio was also greater.

As an example, the following images show the results after compression and decompression using the three algorithms mentioned above.

Image 1: original image

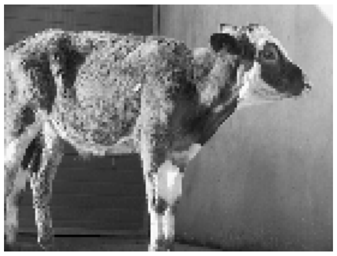


Image 2: Compressed image using Nearest Neighbor

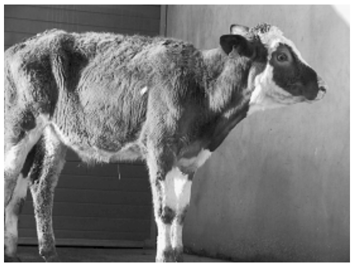


Image 3: compressed image using LZ77 algorithm

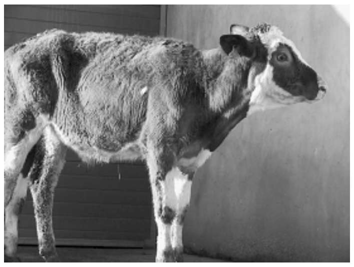


Image 4: Compressed image using Huffman Coding

1.3 Article structure

In what follows, in Section 2, we present related work to the problem. Later, in Section 3, we present the data sets and methods used in this research. In Section 4, we present the algorithm design. After, in Section 5, we present the results. Finally, in Section 6, we discuss the results, and we propose some future work directions.

2. RELATED WORK

In what follows, we explain four related works on the domain of animal-health classification and image compression in the context of PLF.

2.1 Cloud Services Integration for Farm Animals' Behavior Studies Based on Smartphones as Activity Sensors

This work was based on using smartphones, particularly iPhone 4s and 5s, as sensors to study animal behavior in the context of PLF, due to the fact that it provides valuable information on their health, performance and reproductive status. The factors that were studied include their location obtained by GPS, and the low and high frequency components of behavior as posture of the animal. In order to compress the images and data, the compression algorithms they used were LZ4 by default or LZF. Furthermore, they concluded that the compressibility of data massively acquired can be reduced by 43.5% on average, while individual parameters can be highly compressible. Finally, they mention that other data compression algorithms must be considered to optimize energy consumption of the battery. [9]

2.2 An Animal Welfare Platform for Extensive Livestock Production Systems

This study was focused on presenting a solution for monitoring and tracking animal activity and behavior in livestock farms by using wireless sensors to record animal activity, edge computing devices with computational capabilities (offline and real time data processing), cloud computing and usable and effective visualizations in mobile devices. Additionally, to develop an automated system with a single wireless sensor, it uses Deep Neural Network pattern recognition algorithms, which have a low implementation cost. Their results include the necessity to minimize the amount of transmitted data on the wearable device in order to optimize battery lifetime. [12]

2.3 Visual Localisation and Individual Identification of Holstein Friesian Cattle via Deep Learning

In this article, they use computer vision pipelines that use deep neural architectures to automate Holstein Friesian cattle detection and identification in agriculture. To pull off their project, they used fixed and mobile camera platforms, and later brought in video processing pipelines. Finally, they demonstrated that Friesian cattle detection and localization can be performed with a 99.3% accuracy rate, and by using the video processing pipeline they showed and accuracy of 98.1% with 23 individuals. [1]

2.4 Animal Sound… Talks! Real-time Sound Analysis for Health Monitoring in Livestock

This study uses sound based PLF techniques to monitor pigs' health, which can have many advantages over other types of techniques, such as the fact that they are contactless, relatively cheap, and only one sensor can be used for large groups of animals. They used a respiratory distress monitor in order to monitor the respiratory health of pigs. Hence, the implementation of analyzing algorithms was necessary to identify if a pig's cough was pathological or non-pathological. They concluded that this tool could work to give early warning (about 2 weeks before) compared to human observations. [7]

3. MATERIALS AND METHODS

In this section, we explain how the data was collected and processed and, after different image-compression algorithm alternatives to solve improve animal-health classification.

3.1 Data Collection and Processing

We collected data from Google Images and Bing Images divided into two groups: healthy cattle and sick cattle. For healthy cattle, the search string was "cow". For sick cattle, the search string was "cow + sick".

In the next step, both groups of images were transformed into grayscale using Python OpenCV and they were transformed into Comma Separated Values (CSV) files. It was found out that the datasets were balanced.

The dataset was divided into 70% for training and 30% for testing. Datasets are available at https://github.com/mauriciotoro/ST0245-Eafit/tree/master/proyecto/datasets.

Finally, using the training data set, we trained a convolutional neural network for binary image-classification using Google Teachable Machine available at https://teachablemachine.withgoogle.com/train/image.

3.2 Lossy Image-compression alternatives

In what follows, we present different algorithms used to compress images.

3.2.1 Seam carving

Seam carving, developed by Shai Avidan and Ariel Shamir, consists of establishing seams (paths of pixels) either horizontally or vertically to remove rows or columns of an image. This algorithm has only a local effect and shifts the remaining pixels left or up to compensate for the missing ones. To achieve this, each pixel on the image has a value for its energy, and dynamic programming is used to find seams through the following steps. Fist, each pixel in the first row/column keeps its energy as there are no rows/columns before. Then, from the second row/column to the last one, its energy is computed with the cumulative minimum energy for all the possible connected seams of the row/column before. Finally, the minimum energy value found will indicate the seam that will be removed. [2]

In general, this is a rather simple algorithm that does not require a lot of work; however, when it is used with images with a lot of detail, this strategy will not work appropriately. [3]

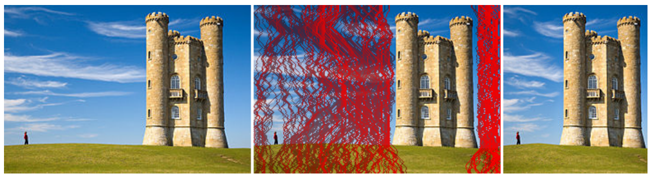


Figure 1: Seam Carving process diagram

3.2.2 Image scaling

Image scaling, or image interpolation, resizes an image from one resolution to another one by using geometric transformations of each pixel without losing the content and quality of the image. There are different algorithms used to scale an image, such as Bilinear, Bicubic, Nearest-Neighbor, Bicubic, Cubic B-spline and Lanczos. We will explain how Nearest-Neighbor and Bilinear work. [20]

<u>Nearest-Neighbor:</u> it is the simplest algorithm of all as it only considers the nearest pixel to fill the empty spaces and replicates it as the image grows. It is very efficient, as it requires the least computation and processing time, but the quality of the image created is very poor. [17]

<u>Bilinear:</u> it identifies the distance from the four nearby pixels in an image and takes the distance-weighted average of these four pixels to determine a new value, and a new pixel is estimated with the relative distance of the nearby pixels. This algorithm results in smoother images than Nearest-Neighbor but will also have a blurring effect. Finally, as it takes more pixels, it requires more processing time and produces better outputs. [17]

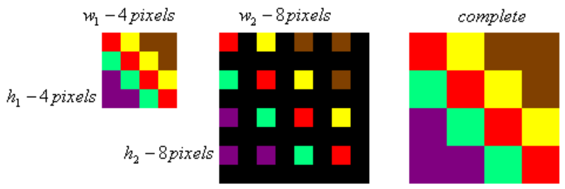


Figure 2: Image scaling using nearest-neighbor

3.2.3 Fractal compression

Fractal compression consists of representing an image using fractals, which is then represented by IFS (iterated function systems), a group of affine transformations. In order to achieve this, the image is split up into different segments that help to find similarities easier. Its main goal is to find the affine transformation for each fractal, and later look for the fractal that can be the best fit to the original image.

This method is very computationally expensive due to the fact that it looks for similarities in the picture. Because of this, it is not very practical to use in real time applications, as it takes more time and energy. [14]

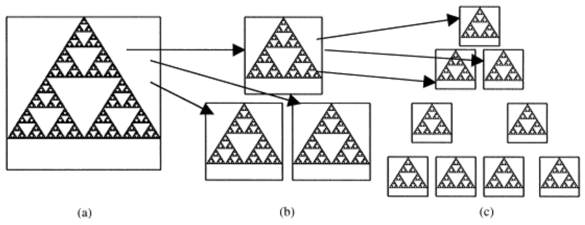


Figure 3: Fractal compression diagram

3.2.4 Discrete cosine transform

The discrete cosine transform (DCT) represents an image as the sum of cosine functions of different frequencies and magnitudes. This method has 3 main steps: quantification, coding and transmission, which work by decomposing an image to its spatial frequency spectrum as a finite sequence. First, the image is decoded into blocks of pixels; then, some of those blocks are discarded using the inverse discrete cosine transform of each one; and finally, the image is reconstructed by putting the blocks back together. [10]

This algorithm is known to have a good capacity of energy compaction, which means that most of the image is divided into a few blocks. Hence, it produces few mistakes in the image compression, creating a clear output. [11]

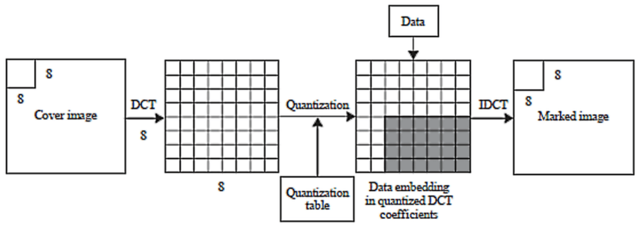


Figure 4: Discrete cosine transform vector figure

3.3 Lossless Image-compression alternatives

In what follows, we present different algorithms used to compress images.

3.3.1 Huffman coding

Huffman coding is based on finding the probabilities of data occurring in the sequence, so symbols that occur less frequently will need more bits than those with less frequencies. To do this, it starts by adding together the two pixels with the lowest probabilities, repeating this process until there is only one pixel left with a total probability of 1. Then, it goes back through the same path and codes each probability with binary code (0 and 1) until it is back at the beginning. [19]

Its time complexity is determined by O(nlogn), where n is the number of unique characters. [16]

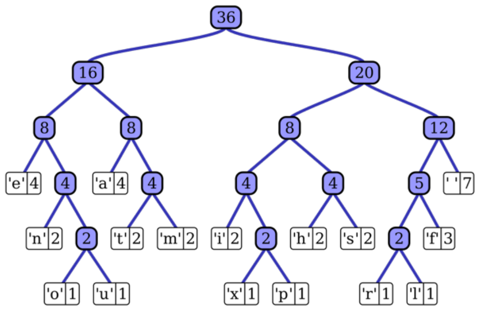
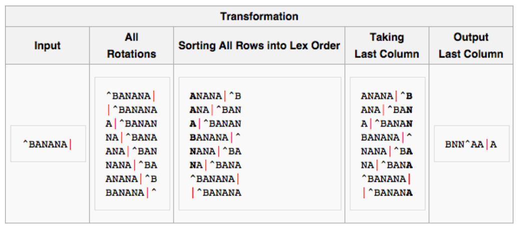


Figure 5: Huffman coding vector figure

3.3.2 Burrows & Wheeler transform

The Burrows-Wheeler transform is based on block sorting lossless data compression algorithms. It consists of transforming a block of data (or pixels) into a form that allows easier compression. It follows the following steps. First, the original sequence is copied to the first row; then, it is sorted with all possible left-cycling permutations in the following rows; after that, rows are sorted lexicographically; and finally, the output is the last column. [18]

This algorithm is known to be very effective, due to the fact that it is reversible, and it doesn't need to store any additional data to achieve this. Its time complexity is determined by the expression O(n). [8]



Transformation				
Input	All Rotations	Sorting All Rows into Lex Order	Taking Last Column	Output Last Column
^BANANA|	^BANANA|	ANANA|^B	ANANA|^B	BNN^AA|A
	|^BANANA	ANA|^BAN	ANA|^BAN	
	A|^BANAN	A|^BANAN	A|^BANAN	
	NA|^BANA	BANANA|^	BANANA|^	
	ANA|^BAN	NANA|^BA	NANA|^BA	
	NANA|^BA	NA|^BANA	NA|^BANA	
	ANANA|^B	^BANANA|	^BANANA|	
	BANANA|^	|^BANANA	|^BANANA	

Figure 6: Burrows and Wheeler transform implementation

3.3.3 LZ77

The LZ77 Compression Algorithm is based on replacing redundant information with metadata (data that describes other data). To do this, sections that are identical to others that have already been encoded are replaced by metadata that includes information on how to expand those sections again. Firstly, the algorithm looks for the window with the longest match to the beginning of the lookahead buffer (the byte sequence from the actual coding position to the end of the input stream) and outputs a pointer to that match. If a match is not found, the algorithm outputs a null-pointer and the byte at the coding position. [15]

The time complexity of this algorithm is determined by the expression O(n), where n is the size of the input stream. Additionally, a huge advantage of this algorithm is that the backward process (decoding) is very simple and fast. Due to this, LZ77 is best for a file that is going to be encoded 1 time and decoded many times. [4]

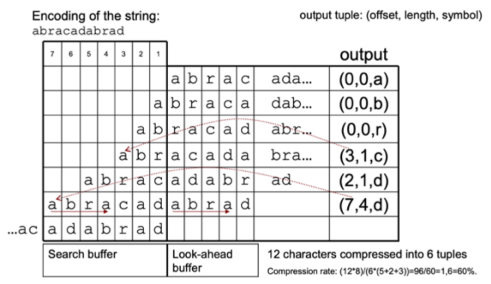
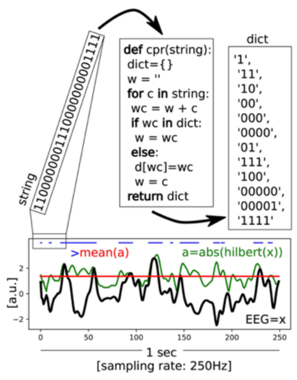


Figure 7: LZ77 example diagram

3.3.4 LZS

The LZS algorithm combines the LZ77 compression algorithm and Huffman coding. It looks for repeated data in the input data and replaces them with encoded tokens that are shorter. When a match between previous encoded data is found, it creates another encoded token that points to the match. Then, the encoded tokens replace redundant data into compressed streams. To do this, it maintains a compression history of 2 kilobytes of raw input data and other data structures that accelerate the process.

In addition, when there is more repetition of data, the compression ratio is higher, and vice versa. Thus, compression ratio is the quotient between the number of input bytes by the number of output bytes, so the less output bytes, the higher the compression ratio. [13]



```
def cpr(string):
 dict={}
 w = ''
 for c in string:
  wc = w + c
  if wc in dict:
   w = wc
  else:
   d[wc]=wc
   w = c
 return dict
```

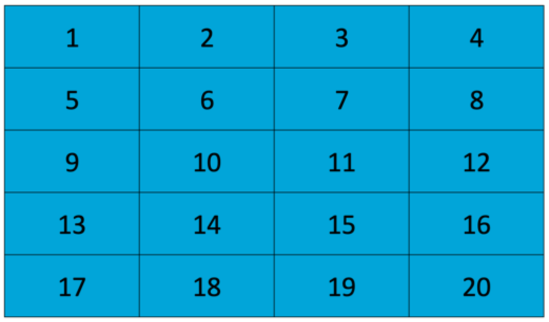
Figure 8: LZS vector figure

4. ALGORITHM DESIGN AND IMPLEMENTATION

In what follows, we explain the data structures and the algorithms used in this work. The implementations of the data structures and algorithms are available at Github[1].

4.1 Data Structures

For the lossy image compression algorithm, we used a matrix, or a rectangular array, of size $m * n$, where m is the number of rows, and n is the number of columns. Each position of the matrix represents a pixel of the image. Additionally, its size is fixed depending on the dimensions of the image, and any position can be accessed by giving the specific row and column number. For the implementation of our algorithm, we only need to access certain positions of the matrix, which has a time complexity of $O(1)$, so this data structure is very efficient for this purpose.



1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20

Figure 9: representation of a matrix with size 5x4 (5 rows, 4 columns).

In contrast, the main data structure used for the lossless image compression algorithm was the Huffman tree, a full binary tree in which each of its leaves corresponds to a pixel in the image. In this tree, a heap queue (stores each node from smallest to greatest) is used to store the frequency of each node, and pixels that occur less frequently are located in the bottom of the tree. In addition, the father of each leaf is the sum of its frequency and its neighbor leaf, and for every node that is not a leaf, its left edge is marked with 0 and its right edge with 1. In order to add an element to the tree, there is a time complexity of $O(\log n)$, which is a rather efficient time complexity.

[1]https://github.com/mjbernalv/ST0245-001/tree/master/proyecto

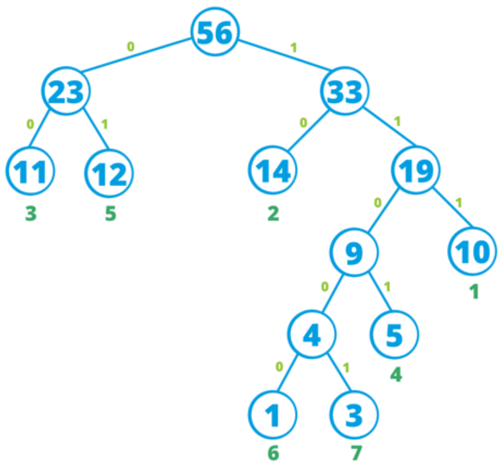


Figure 10: Representation of an image with dimensions 7x8 in a Huffman Tree

4.2 Algorithms

In this work, we propose a compression algorithm which is a combination of a lossy image-compression algorithm and a lossless image-compression algorithm. We also explain how decompression for the proposed algorithm works.

The algorithm we used to implement the lossy image compression was image scaling, precisely Nearest Neighbor, and for the lossless image compression we used Huffman coding.

4.2.1 Lossy image-compression algorithm

Image compression using Nearest Neighbor selects certain pixels of the image, or positions in the matrix, depending on the amount of compression that wants to be done (ratio), and copies those values into a new matrix that will have a size of $\frac{m}{ratio} * \frac{n}{ratio}$, which is clearly smaller than the original image.

In order to do this, we implemented an algorithm that takes two parameters as arguments, which are the image that wants to be compressed, and the ratio which will determine how much it will be reduced (must be greater or equal to 1). After that, it creates an empty matrix with the new size (depends on the ratio), which will be filled with certain pixels of the original image. To choose the pixels, it iterates through the whole original matrix from the beginning and advances at a rate equal to the ratio in rows and columns. The values in the positions accessed are then added to the new matrix, which corresponds to the compressed image.

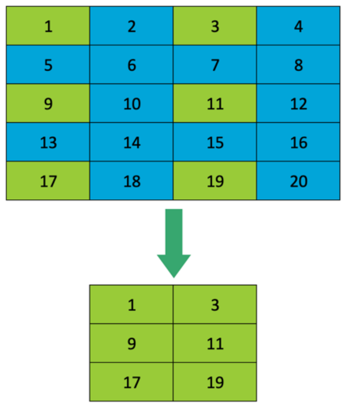


Figure 11: diagram explaining how compression using Nearest Neighbor algorithm works. In this case, ratio is equal to 2.

Image decompression using Nearest Neighbor replicates the values in a matrix, or pixels in an image, by a certain ratio, and copies them to a new matrix that will have a size of $(m \times ratio) * (n \times ratio)$, which is bigger than the original image.

Our algorithm takes two parameters as arguments, the original image that will be decompressed and the ratio that indicates how much it will be expanded (must be greater or equal to 1). A new empty matrix with the new size will be then created, and the original image will be iterated, where each pixel will be reproduced in a rectangle of size $ratio * ratio$ in the matrix in the same relative position of the original one.

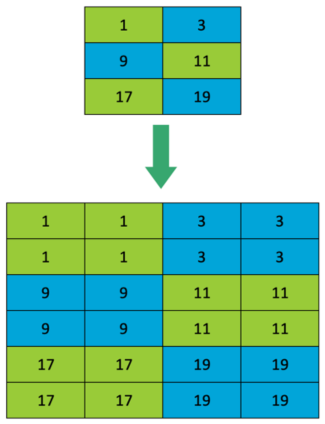
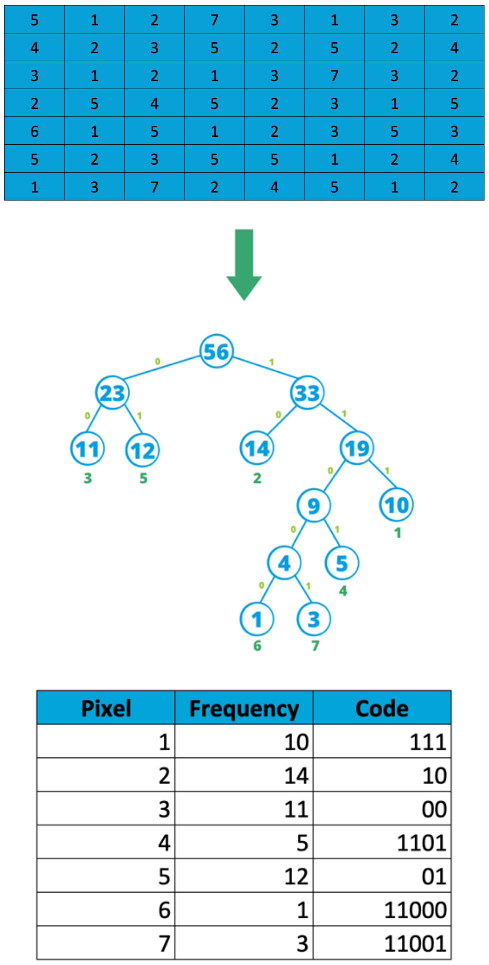


Figure 12: diagram explaining how decompression using Nearest Neighbor algorithm works. In this case, ratio is equal to 2.

4.2.2 Lossless image-compression algorithm

Image compression using Huffman coding creates a tree, known as Huffman tree, that stores the frequencies of the different pixels of an image using heaps.

To achieve this, it starts by counting the frequencies of each pixel in the image and stores them in a hash table. Then, these pixels are moved to a heap queue, which stores them according to their frequencies, sorting them in increasing order. After that, the tree is created, starting by getting the two first pixels with less frequencies and generating a new node that has a frequency of the sum of both frequencies, which will have the smallest pixel in the left and the largest one in the right. This process continues until all the pixels are removed from the heap queue. Additionally, the left edge of each node of the tree is assigned a value of 0, and the right one a value of 1. Subsequently, the route from the tree's root to each pixel, which are all the leaves, is coded by traversing the whole tree and creating a string with zeros and ones, and it is stored in a hash table. Later, the input image, or csv file, is encoded, and if its code (route) is not a multiple of 8, it is padded. Finally, this padded information is stored in 8 bits, and it is saved in a bit array, which is later converted to a csv file. This will be our compressed file.



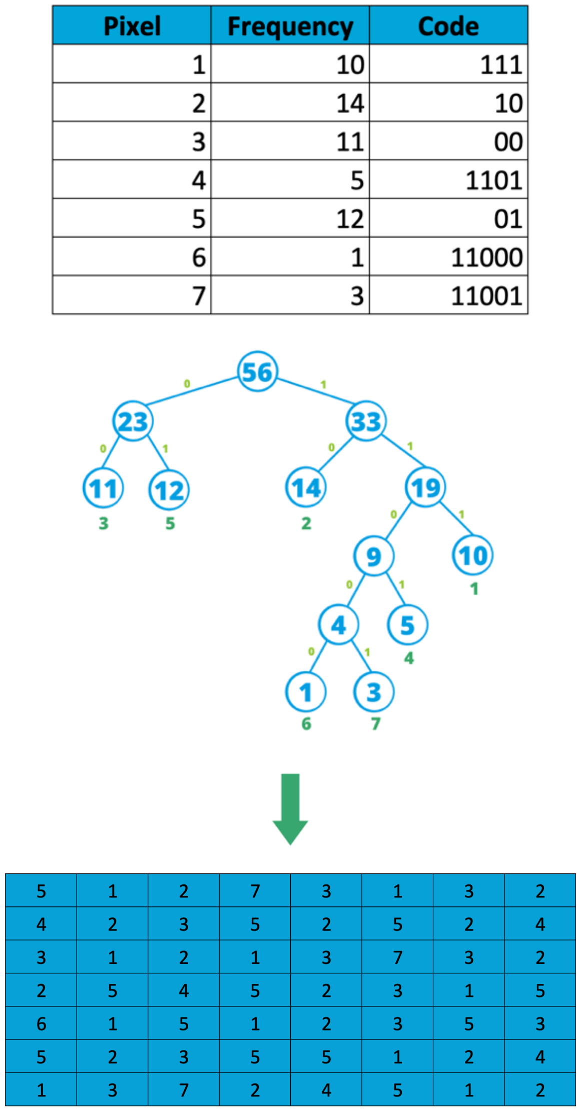
5	1	2	7	3	1	3	2
4	2	3	5	2	5	2	4
3	1	2	1	3	7	3	2
2	5	4	5	2	3	1	5
6	1	5	1	2	3	5	3
5	2	3	5	5	1	2	4
1	3	7	2	4	5	1	2

Pixel	Frequency	Code
1	10	111
2	14	10
3	11	00
4	5	1101
5	12	01
6	1	11000
7	3	11001

Figure 9: Huffman coding compression example with an image of dimensions 7x8. Initially, the image's initial size was 448 bits, and after compression it was 256 bits (compression ratio 1.75 : 1).

On the other hand, for decompression, Huffman coding reverses the process done in compression, without losing any data.

To be able to do this, it starts by reading and translating the compressed file. Then, padding is removed from the file, so that the decoding process can take place, which is in charge of reconstructing the Huffman tree and creating a new csv file that is identical to the original image.



Pixel	Frequency	Code
1	10	111
2	14	10
3	11	00
4	5	1101
5	12	01
6	1	11000
7	3	11001

5	1	2	7	3	1	3	2
4	2	3	5	2	5	2	4
3	1	2	1	3	7	3	2
2	5	4	5	2	3	1	5
6	1	5	1	2	3	5	3
5	2	3	5	5	1	2	4
1	3	7	2	4	5	1	2

Figure 10: Huffman coding decompression example with an image of dimensions 7x8.

4.3 Complexity analysis of the algorithms

In order to calculate the time complexity for the worst case in both algorithms, we started by analyzing each line's complexity, and using the big O notation rules to obtain the final complexity. Additionally, the worst case for both algorithms is when all the pixels of the image have a different value.

Lossy algorithm	Time Complexity
Compression	$O(n * m)$
Decompression	$O(n * m)$

Table 2: Time Complexity of the image-compression and image-decompression algorithms using Nearest neighbor, where n is the number of columns and m the number of rows of the image.

Lossy algorithm	Memory Complexity
Compression	$O(n * m)$
Decompression	$O(n * m)$

Table 3: Memory Complexity of the image-compression and image-decompression algorithms using Nearest neighbor, where n is the new number of columns and m the new number of rows of the image.

Lossless algorithm	Time Complexity
Compression	$O((n * m)\log(n * m))$
Decompression	$O((n * m)\log(n * m))$

Table 4: Time Complexity of the image-compression and image-decompression algorithms using Huffman coding, where n is the number of columns and m is the number of rows.

Lossless algorithm	Memory Complexity
Compression	$O(p)$
Decompression	$O(p)$

Table 5: Memory Complexity of the image-compression and image-decompression algorithms using Huffman coding, where p is the number of unique pixels of the image.

4.4 Design criteria of the algorithm

4.4.1 Lossy image-compression algorithm

In order to choose the Nearest neighbor algorithm for lossy image-compression, we started by looking and comparing different image scaling algorithms, such as Nearest neighbor, bilinear, and bicubic, and after checking some image outputs, we realized that Nearest neighbor had a relatively good image output taking into account that it is a lossy compression algorithm, as the quality of the new image was clearer than the other (less blur). Furthermore, it has somewhat good time complexity, which is $O(n * m)$, meaning that each pixel in the matrix will be iterated at most one time. In original image's matrix, the only operation that has to be done during the algorithm is to access a certain position or pixel, which has a constant time complexity of $O(1)$, making the matrix a very efficient data structure for this purpose. Contrarily, memory complexity in this algorithm is also $O(n * m)$, which means that it is also a very efficient algorithm, as it only requires this new space.

4.4.1 Lossless image-compression algorithm

For the lossless image-compression algorithm, we chose Huffman coding after comparing it with LZ77. By testing, for example, compression and decompression of a 201KB image, LZ77 took about 15 seconds to compress and 3 minutes and 15 seconds to decompress, while Huffman Coding only took 0.08 seconds to compress and 0.16 seconds to decompress, which shows a significant difference in time consumption. In addition, while the compressed file using LZ77 had a file size of 137KB, Huffman coding had a file size of 81KB, which shows a higher compression ratio for Huffman coding. After analyzing these results, we decided to use Huffman coding, an algorithm that proved to be more efficient in terms of time and memory consumption.

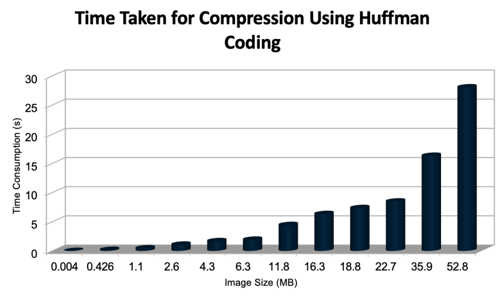
5. RESULTS

5.1 Execution times

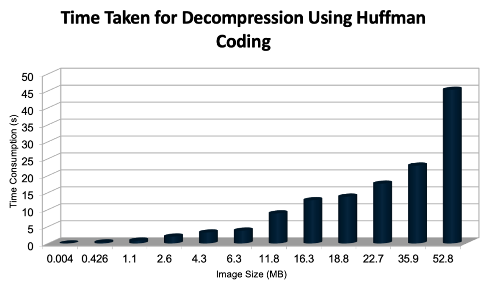
In what follows we explain the relation of the average execution time and average file size of the images in the data set, in Table 6.

	Average execution time (s)	*Average file size (KB)*
Compression	6.36 s	14.42 MB
Decompression	10.96 s	14.42 MB

Table 6: Execution time of Huffman coding algorithm for both compression and decompression.



Graph 1: Bar graph illustrating time taken for compression using Huffman Coding.



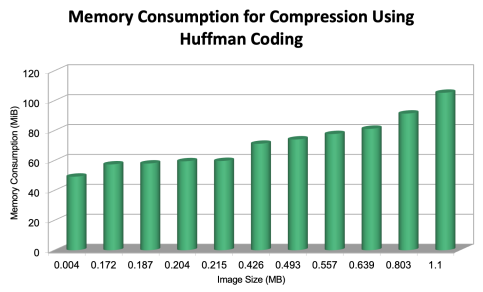
Graph 2: Bar graph illustrating time taken for decompression using Huffman Coding.

5.2 Memory consumption

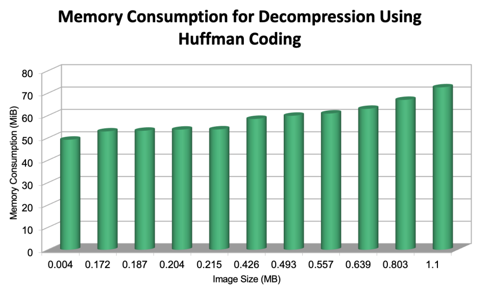
We present memory consumption of the compression and decompression algorithms in Table 7.

	Average memory consumption (MiB)	*Average file size (MB)*
Compression	71.34 MiB	0.44 MB
Decompression	58.61 MiB	0.44 MB

Table 7: Average Memory consumption using Huffman coding for both compression and decompression.



Graph 3: Bar graph illustrating memory consumption for compression using Huffman Coding.



Graph 4: Bar graph illustrating memory consumption for decompression using Huffman Coding.

5.3 Compression ratio

We present the average compression ratio of the compression algorithm in Table 8.

	Healthy Cattle	*Sick Cattle*
Average compression ratio	2.6 : 1	2.8 : 1

Table 8: Rounded Average Compression Ratio of images of Healthy Cattle and Sick Cattle using Huffman coding.

6. DISCUSSION OF THE RESULTS

After working with three different algorithms for compression and decompression of images, specifically Nearest neighbor, Huffman Coding and LZ77, we can clearly see that the best algorithm for the purpose of animal-health classification in the context of Precision livestock farming is Huffman coding. This is due to the fact that, apart from being a lossless image compression algorithm, it has a relatively good time and memory complexity, as the amount of time and memory used is better than both of the other algorithms. Additionally, compression ratio is also very good for both, sick and healthy cattle.

Some advantages of this algorithm are the facts that it is fast, uses little memory, and has a very effective compression ratio, which is very appropriate. However, it may be an algorithm that is hard to understand and requires more knowledge of computational terms, so people that don't have a basic education on these topics may find it hard to comprehend.

Finally, we consider that this algorithm may be very useful for the purpose of optimizing energy consumption in the context of PLF, taking into account all its advantages and the fact that it is a lossless image compression algorithm, so no data will be lost.

6.1 Future work

In the future, we would like to merge different compression and decompression algorithms, such as the ones used in this work, with the objective of producing a better and more efficient way of compressing images for PLF. This could improve time and memory consumption and compression ratio, making it much more efficient.

In addition, we would like to test our algorithms with a convolutional neural network for binary image-classification to see how efficient, accurate and sensitive they are.

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