[1] **Julissa Elizabeth Reyna-Gonzalez**

[2] **Jorge Rubén Hilario Cárdenas**

[3] **Janeth Leynig Tello Cornejo**

[4] **Marco Alberto Suárez Pozo**

[5] **Ines Eusebia Jesús Tolentino**

Artificial Selection Program for the Improvement of Genetics in Bovine Animals

Abstract: - The present work focuses on the study of animal genetic improvement in bovines of the city of Huánuco with genetic algorithms which will help to improve in each new generation of bovine calves both the physical characteristics and adaptation to new environments, also in improving meat and milk.

Evaluate productive records of animals with multiple crossings to determine differences at the productive level. The data that belong to bovines with multiple racial component belonging to the Huánuco farms dedicated to the production of meat and milk. The high dispersion of the offspring values and the high genetic correlation between the evaluated traits allowed the identification of animals with high genetic merit, meriting their potential use as parents of the next generation.

All of this will serve as a reference for new care processes in raising and feeding bovines.

Keywords: Artificial selection, genetic improvement, bovine animals, Characteristics, adaptation.

I. INTRODUCTION

Currently, there exist over 1000 distinct cattle breeds with various purposes, including dairy production, meat, leather, and even for religious or recreational use. The breeding of these cattle has led to the development of different improvement strategies over time. Depending on the selection criteria applied to these animals, the livestock industry in the city of Huánuco aims to enhance meat and milk production through crossbreeding. However, this has had the unintended consequence of diluting the purity of the breeds, resulting in a decline in both the quality and quantity of output. This, in turn, directly impacts the profitability of the cattle industry.

With the advancement of technology today, it is now feasible to employ an algorithm to select optimal specimens for crossbreeding. This approach ensures the creation of cattle with the best traits from their respective populations. Consequently, the goal is to ensure the certainty of obtaining superior cattle, ultimately leading to an improvement in the quality of both meat and milk produced by cattle in the city of Huánuco.

The quantification of a population's genetic advancement can be determined by assessing its response to selection or genetic inclination. The latter assesses the genetic alterations achieved through the selection process over time (Larios, et al., 2020). Biotechnologies like AI Artificial Insemination and IATF Fixed Time Artificial Insemination have been crafted primarily for enhancing genetics within the livestock sector (Marizancen, 2017). The main aim of this research was to implement an artificial selection program utilizing genetic algorithms to enhance the genetic qualities of bovine animals. Specific goals included the identification of key characteristics in the targeted bovine population for genetic enhancement.

In their 2021 article, Zuñiga et al. highlight the growing importance of sheep production in Costa Rica, emphasizing the need for extensive information exchange and local research development. Scarce access to relevant local data impedes the development of new sheep breeds with superior attributes and genetic improvements. This review addresses various genetic foundations to facilitate the establishment of a sheep genetic enhancement program. Several selection methods are described, and proposals are presented for different sheep crosses aimed at producing genetically superior animals. While these suggested crosses are intended to be

[1] Professor at the Universidad Nacional Hermilio Valdizán-Huánuco, Perú. jreyna@unheval.edu.pe
[2] Professor at the Universidad Nacional Hermilio Valdizán-Huánuco, Perú. jrhilario@unheval.edu.pe
[3] Professor at the Universidad Nacional Hermilio Valdizán-Huánuco, Perú. jtello@unheval.edu.pe
[4] Professor at the Universidad Nacional Hermilio Valdizán-Huánuco, Perú. msuarez@unheval.edu.pe
[5] Professor at the Universidad Nacional Hermilio Valdizán-Huánuco, Perú. ijesus@unheval.edu.pe

conducted with sheep species already present in Costa Rica, they can be applicable in other regions with similar improvement objectives.

Galeano,(2020) in his research affirms that the area of genetics and improvement is constituted as one of the fundamental pillars within the training process of students of the professional program in Zootechnics, since it represents one of the main planning and management tools. of agricultural companies worldwide; however, with regard specifically to the branch of quantitative genetics, it is rare to find bibliographic material that manages to gather the main concepts, foundations and methodologies related to the implementation of breeding programs in different animal production systems. In this context, the following support material has been designed as a literature review, which compiles the approaches made by some of the most relevant authors in this area of knowledge. Initially, the fundamental concepts and bases that frame the development of improvement programs in animal production systems are presented, whose stages are broken down in a specific and detailed manner in each of the chapters that are part of this Campus Note.

Flatten & González (2021), in their paper titled "Comparing and Choosing Artificial Intelligence Approaches for Predicting Bovine Milk Production," assert that forecasting plays a crucial role in decision-making, particularly within the dairy industry. These forecasts significantly enhance dairy herd management, reduce energy consumption on farms, and optimize long-term capital investments. The utilization of artificial intelligence techniques to predict milk yields has garnered considerable interest within the scientific community. However, determining an efficient technique or model for forecasting milk production across diverse settings poses a formidable and intricate challenge, as no single approach proves accurate in all scenarios.

In their study, the authors compared various artificial intelligence techniques employed in the literature for predicting bovine milk production and employed the Hierarchical Analysis Process to select the approach with the best fit for these forecasts. They employed synthetic analytical, survey, and experimental methods as part of their scientific inquiry. The findings identified Artificial Neural Networks as the most suitable artificial intelligence approach for forecasting bovine milk production, surpassing Decision Trees and Support Vector Machines. The research determined that the key selection criteria in the dairy production domain revolve around these techniques' capacity to handle uncertain data and generate precise results optimally. The analysis conducted lends substantial support to decision-making processes within milk-producing organizations.

Parra et al., (2023) in their research work entitled "Assisted genetic improvement for reproductive characteristics of domestic animals" it is concluded that reproductive characters may be even more important than productive ones, given the implications they have on the biological efficiency of production systems. However, due to different factors, the proportion of phenotypic variability that can be used for selection using conventional methods is low, therefore the use of genetic markers is a current possibility. A large number of genetic markers, especially of the SNP type, have been tested with an effect on some reproductive characteristics in cattle and especially sheep. The use of these tools does not imply the elimination of traditional methods,

II. RESEARCH DESIGN AND METHOD

Design of the investigation

The research will have the character of an experimental design.

Hypothesis

Hi: The artificial selection program using genetic algorithms significantly improves genetics in bovine animals.

Ho: The artificial selection program does not significantly improve genetics in bovine animals.

Goals

General

Implement an artificial selection program using genetic algorithms to improve genetics in bovine animals.

Specific

Identify the relevant characteristics of the bovine under study for genetic improvement in bovine animals.

Design an artificial selection program using genetic algorithms for genetic improvement in bovine animals.

Validate the artificial selection program using genetic algorithms for genetic improvement in bovine animals.

Study variables

Dependent variable:

Artificial selection

Artificial selection is an evolutionary process by which humans consciously select, for or against, certain characteristics of organisms. (Understanding Evolution, 2022)

Independent variable:

Bovine genetic improvement

Bovine genetic improvement is a process that focuses on selecting and reproducing animals with desirable characteristics in order to improve the quality of cattle. (Flatten & Gonzalez, 2021)

Type

According to the orientation, the present work is of an applied type, because we will apply knowledge to solve problems of reality according to the contrasting technique.

Population and sample

We will work with a defined population of bovines that will consist of 100 farmers.

POPULATION	PLACE
100	populated centers of Alcas and Matihuaca, in the province of Ambo, around Huánuco.

A. Sample

Sample calculation for research:

$$n = \frac{N * Z_a^2 * p * q}{d^2 * (N-1) + Z_a^2 * p * q}$$

N = population size
Z = confidence level
P = probability of success, or expected proportion
Q = probability of failure
D = precision (Maximum admissible error in terms of proportion).

$$n = \frac{100 \times 1.96^2 \times 0.5 \times 0.5}{0.05^2 \times (100-1) + 1.96^2 \times 0.5 \times 0.5}$$

$$n = 80$$

It will work with a sample of 80 Ranchers.

Data collection techniques and instruments

Techniques

- Survey

Instrument

Questionnaire: Ordinal and Nominal

- Closed questions
- Open questions

Data analysis methods

Tabulation

The tabulation of the data by counting the responses contained in the instruments, a count and assignment of numerical codes obtained from the surveys will be carried out.

Electronic tabulation: The data to be tabulated will be processed electronically, since they are relatively large numbers, through Excel or computer packages that facilitate the creation of simple statistical tables or tables (with one variable) and crossovers (two or more variables).

III. RESULTS

Statistical results:

Figure 1

The result is that 16 farmers, equivalent to 19.5%, do not have prior knowledge about how correct selective breeding is carried out.

It was obtained that 66 farmers, equivalent to 80.5%, have previous knowledge on how to carry out a correct selective breeding.

The results indicate that there is a large number of farmers from the Huánuco population who have knowledge about selective breeding.

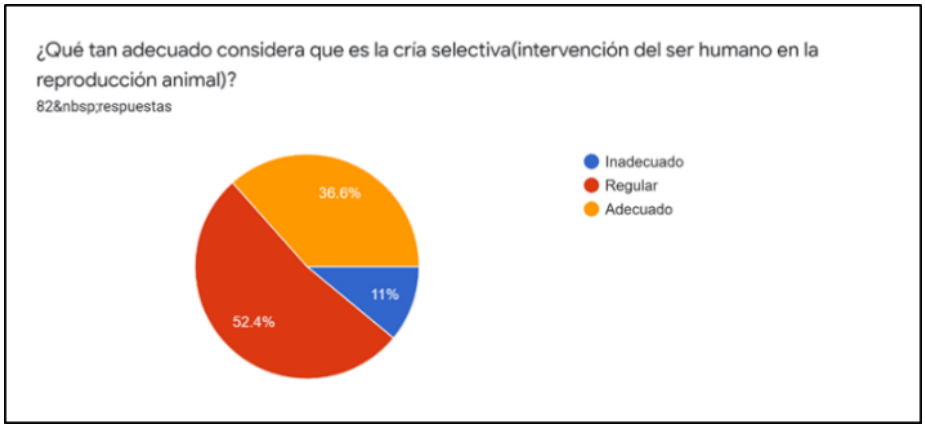


Figure 2

The survey results indicate that there are a large number of winners who consider selective breeding to be appropriate.

- 42 farmers consider it appropriate to carry out the selective breeding technique.
- 29 farmers consider that performing the selective breeding technique is regular.
- 11 farmers consider selective breeding to be an inappropriate technique.

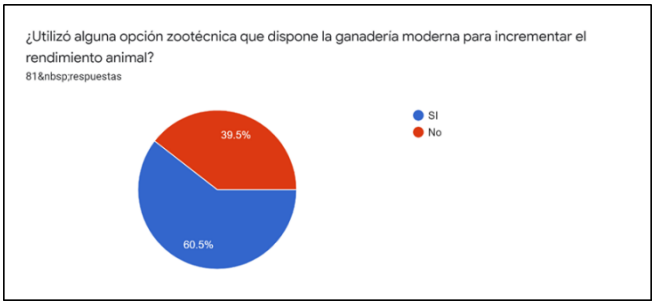


Figure 3

The results of the survey indicate that 49 farmers used zootechnical methods to increase the performance of their cattle.

The survey results indicate that 78 farmers want to increase their productivity and improve the characteristics of their livestock, which is a favorable result for the research.

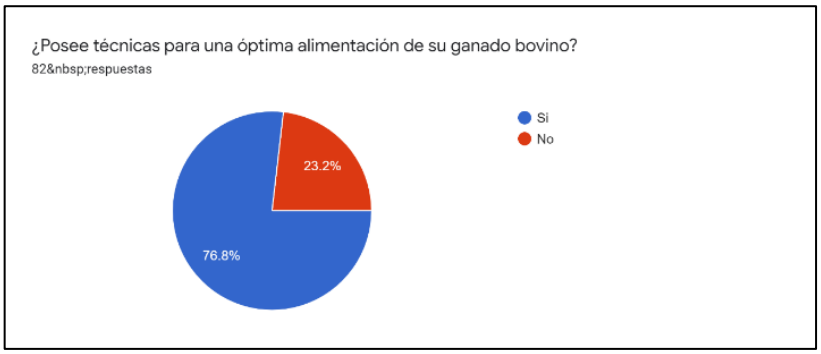


Figure 4

Figure 5

The survey results indicate that 62 farmers use techniques to optimize livestock feeding.

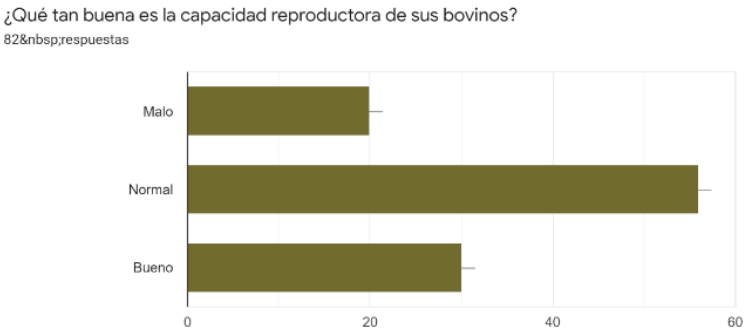


Figure 6

The survey results indicate that:
20 farmers have problems with the reproductive capacity of their cattle.
30 farmers have cattle with good reproductive capacity.
32 farmers have cattle with normal reproductive capacity.

Figure 7

The results indicate that:
32 farmers indicate that the care by the farmer is adequate.
7 farmers indicate that care by the farmer is inadequate.
43 farmers indicate that care by the farmer is adequate.

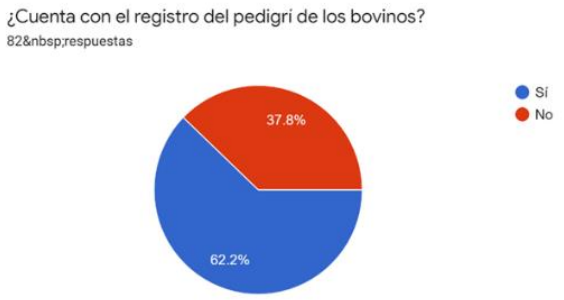


Figure 8

The results indicate that:
31 farmers do not have the pedigree record of their cattle.
51 farmers have the pedigree record of their bovines, which indicates that they have authentic breed bovines.

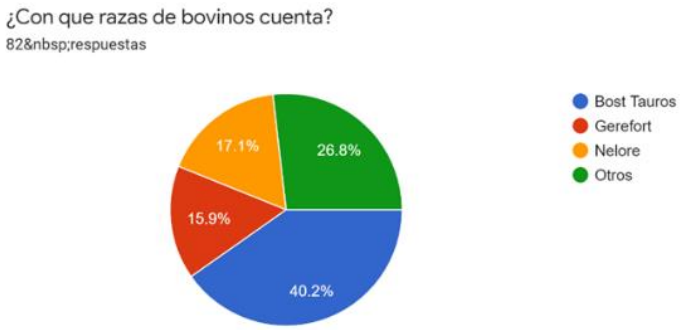


Figure 9

The results indicate that:
22 farmers have breeds other than surveys.
14 farmers have Melare cattle.
13 farmers have Gerefort cattle.
33 farmers have bovines of the Bost Turos breed.

Figure 10

The results indicate that:
15 farmers consider the climate of Huánuco unsuitable for raising and reproducing cattle.
67 farmers consider that the climate of Huánuco is suitable for raising and reproducing cattle.

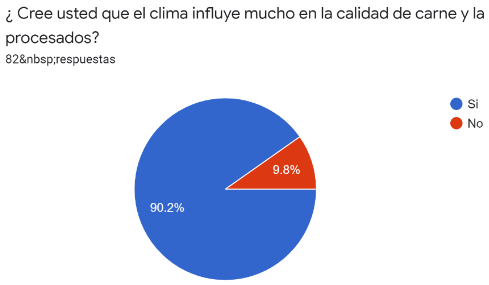


Figure 11

The results indicate that:

8 farmers consider that the climate of Huánuco does not influence or has a non-significant influence on the quality of meat and milk at the time of processing.

74 farmers consider that the climate of Huánuco significantly influences the quality of meat and milk at the time of processing.

Answers and system development

Representation of the artificial selection of bovines:

- Pedigree representation: The code consists of 1 digit; the margins of the class can go from 1 to 2.
  Example:

pedigree types	class code
Authentic	1
Hybrid	2

- Food Representation: The code will be made up of 1 digit, the margins of the class can go from 1 to 3.
  Example:

Type of food	Food Code
Grass	3
Corn	2
grain sorghum	1

- Coat Representation: The code will be made up of 1 digit, the margins of the class can go from 1 to 3.
  Example:

coat type	coat code
Simple	3
double or binary	2
Triple	1

- Representation of races: The code will be formed by 1 digit; the margins of the class can go from 1 to 4.
  Example:

Breed Type	Breed Code
Romagnola	4
nelore	3
Gerefort	2
Bost Tauros	1

- Representation of Reproducibility: The code will be formed by 2 digits; the margins of the class can go from 1 to 3.
  Example:

Playability Type	Code
high	1
Half	2
Low	3

- Livestock Representation: The code will be made up of 1 digit, the margins of the class can go from 1 to 4.
  Example:

Type of Farmer	Code
Excellent	1
Well	2
Bad	3
Appalling	4

- Representation of Environmental Condition: The code will be formed by 1 digit; the margins of the class can go from 1 to 3.
  Example:

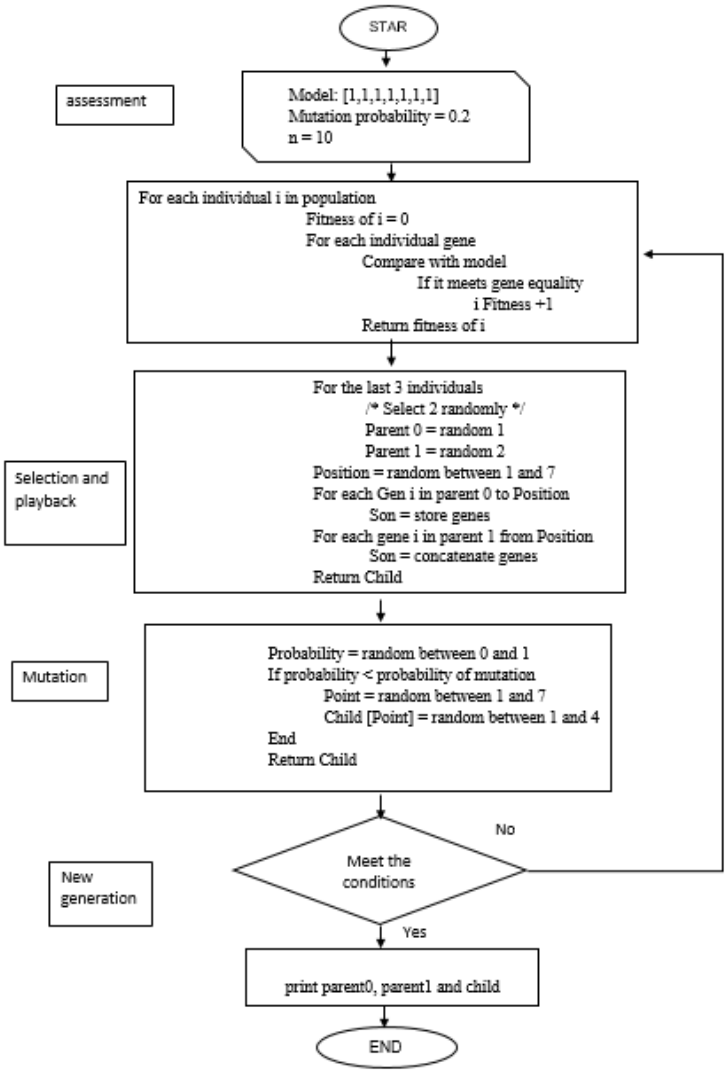
environmental condition	Code
Comfort zone	1
cold zones	2
heat zones	3

pseudocode

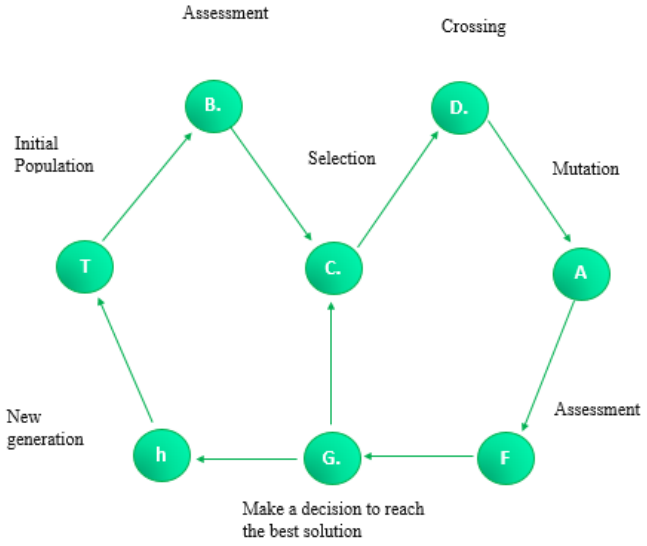
```
Start:
Model: [1,1,1,1,1,1,1]
Mutation probability = 0.2
n = 10
Population:
[[1, 3, 1, 3, 3, 1, 4],
[1, 4, 4, 2, 4, 3, 4],
[1, 3, 2, 2, 2, 4, 2],
[4, 4, 1, 2, 2, 1, 4],
[4, 4, 4, 1, 4, 2, 4],
[1, 2, 4, 2, 2, 1, 4],
[1, 2, 4, 3, 2, 4, 1],
[3, 1, 4, 3, 1, 4, 3],
[4, 4, 1, 1, 1, 3, 3],
[3, 3, 1, 4, 2, 1, 1]  ]
Assessment:
        For each individual i in population
                Fitness of i = 0
                For each individual gene
                        Compare with model
                                If it meets gene equality
                                        i Fitness +1
                        Return fitness of i
                End
        End
end evaluation
Sort out:
        For each individual i, in population
                Sort ASC. by fitness in population
        End
        return population
End Sort
Selection and reproduction:
                For the last 3 individuals
/* Select 2 randomly */
```

```
Parent 0 = random 1
Parent 1 = random 2
End
                    Position = random between 1 and 7
                    For each Gen i in parent 0 to Position
                        Son = store genes
                    End
                    For each gene i in parent 1 from Position
                        Son = concatenate genes
                    End
                    Return Child
End selection and playback
Mutation:
        Probability = random between 0 and 1
        If probability < probability of mutation
            Point = random between 1 and 7
            Child [Point] = random between 1 and 4
        End
        Return Child
end mutation
print parent0, parent1 and child
End
```

Animal Genetic Algorithm Flowchart



Graph



Code

Next, the genetic algorithm of the software developed in Python will be presented, explaining each line and blocks of code to understand its operation. The structure of the program is given by 4 important blocks: initial population; selection and reproduction; mutation; and final population and/or results of the indicated iteration.

The optimal model is a vector of 10 integers that represents an ideal being, it can contain any value, taking into account that this value will be where it is intended to arrive; in this case it is number 1, being considered better than 2, 3 and 4 respectively.

The variable "length" will store the length of the vector, for which it will be 7.

The variable "num" will represent the number of individuals present in both the initial and final population.

The variable "pressure" will be the number of individuals that will be selected for reproduction.

The variable "mutation_chance" is the probability that an individual will mutate, the value of 0.2 is equivalent to 20%.

```
modelo = [1,1,1,1,1,1,1]
largo = 7
num = 10
pressure = 2
mutation_chance = 0.2
```

Source: self-made.

The initial population is printed which is relevant to all processing of the set functions initially provided as data.

```
population = [[1, 2, 4, 1, 3, 1, 4],
    [3, 1, 3, 1, 2, 3, 1],
    [2, 2, 1, 3, 1, 1, 4],
    [3, 3, 3, 3, 2, 4, 4],
    [2, 4, 4, 2, 1, 1, 4],
    [3, 4, 1, 4, 4, 1, 2],
    [3, 4, 4, 1, 4, 3, 1],
    [1, 3, 1, 4, 3, 4, 3],
    [3, 1, 1, 2, 3, 1, 1],
    [2, 1, 3, 4, 4, 3, 2]]

print("Poblacion Inicial: \n%s"%(population))
```

Source: self made.

It continues with the selection and playback function that initially calls the "calculate fitness" function.

The "fitness" is a counter which must be initialized to 0. An individual is taken and each of its values is compared with the model; If an equality with the value 1 is found, the counter will increase by 1, this means that it will count how many values will be equal between the individual and the model. This is done with each individual, having 10 fitness values respectively.

Subsequently, the individuals will be ordered according to their fitness, from lowest to highest; 2 individuals with the highest fitness will be taken for reproduction. Later on, a random number from 1 to 6 will be generated and the 2 selected individuals will be called father [0] and father [1]. The previously generated random number will determine the position of the values of the vector of the child; which will inherit the features(values) from both parent[0] and parent[1] separately. The parents will be printed and this action will be carried out for the other 9 individuals of the following generation, having another random number as position.

```
def calcularFitness(individual):
    fitness = 0
    for i in range(len(individual)):
        if individual[i] == modelo[i]:
            fitness += 1
    return fitness

def selection_and_reproduction(population):
    puntuados = [(calcularFitness(i),i) for i in population]
    puntuados = [i[1] for i in sorted(puntuados)]
    population = puntuados
    selected = puntuados[(len(puntuados)-pressure):]
    for i in range(len(population)-pressure):
        punto = random.randint(1,largo-1)
        padre = random.sample(selected, 2)
        population[i][:punto] = padre[0][:punto]
        population[i][punto:] = padre[1][punto:]
    print("\nPadres:\n%s"%(padre))
    return population
```

Source: self-made.

The third phase that is carried out is that of mutation, a variable with a random number is generated; this number is generated with a decimal value between 0 to 1.

The mutation will be carried out in the event that said value is less than 0.2, for this a random value of the vector (1 to 7) of the individual will be taken and a new value will be assigned randomly from 1 to 4; This action will be carried out for every new individual that would make up a new generation.

```
def mutation(population):
    for i in range(len(population)-pressure):
        variable=random.random()
        if variable<= mutation_chance:
            punto = random.randint(0,largo-1)
            nuevo_valor = random.randint(1,4)
            while nuevo_valor == population[i][punto]:
                nuevo_valor = random.randint(1,4)
            population[i][punto] = nuevo_valor
    return population
```

Source: self-made.

The selection, reproduction and mutation stages will be carried out according to the number of iterations that is desired.

```
for i in range(1):
    population = selection_and_reproduction(population)
    population = mutation(population)
```

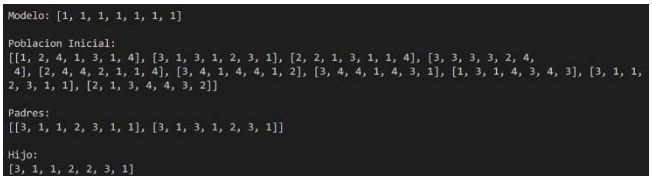
Source: self-made.

The child resulting from the crossover will be printed.

```
print("\nHijo:\n%s"%(population[1]))
```

Source: self-made.

After compiling the entire algorithm, it will show me the following results:



Source: self made.

IV. DISCUSSION

It is imperative to address several critical aspects concerning the estimated genetic parameters in relation to the experimental challenge employed in this study, the theoretical framework, and the proposed hypotheses. According to Van Arendonk, the initial reproductive technique that significantly influenced animal husbandry systems was artificial insemination (AI), along with pedigree and milk registration, aimed at obtaining precise assessments of the animals' productive qualities. Bulls, whether in meat or milk production systems, play a pivotal role in disseminating genetic enhancements by passing down productive traits to their progeny, thereby presenting an appealing economic avenue for advancing the livestock sector. When it comes to the drawbacks associated with genetic algorithms, from a genetic perspective, one limitation is that the response is not solely dependent on genotype-environment interactions, resulting in variability in the long-term expected outcomes. Additionally, inbreeding remains a subject of examination and estimation within the context of genetic improvement. It is anticipated that the introduction and utilization of new generations of foreign semen, along with meticulous record management, will mitigate this risk, which has seen limited progress thus far. The genetic algorithm, through the application and management of biotechnologies, ensures continuous genetic enhancement in livestock over time through crossbreeding involving commercial animals.

For heritability calculations, there would be a high probability that the next generation will have better results than the previous ones and likewise improve even more with the mutations that may occur. In addition, as the estimates that were made on the previous generations will serve as statistical information to see how it improves in each generation and thus see the evolution of the modified animals. So, in this way, it will be possible to have greater control and monitoring regarding animal genetic variation that is being carried out with artificial selection, it will also serve as background for other future research on animal genetic modification in bovines and thus contribute with more information and basis. theoretical.

V. CONCLUSIONS

The artificial selection program using genetic algorithms significantly improves genetics in bovine animals.

It was definitely possible to identify the most suitable bovine and its most relevant characteristics for the process of bovine genetic improvement.

The design of the genetic algorithm for the bovine animal artificial selection process was determined.

We conclude that it is possible to validate the artificial selection program using genetic algorithms for genetic improvement in bovine animals.

VI. RECOMMENDATIONS

The use of this type of algorithms is recommended because they allow us to select and identify the bovines with the best characteristics and thus be able to use them for mating.

It is recommended to use zootechnical methods in the care and breeding of bovines in the city of Huánuco.

The use of this type of algorithms is recommended because they help reduce the time and use of resources to identify suitable specimens to perform the optimal crossing.

This type of algorithm is recommended because it helps us reduce uncertainty when crossing cattle and gives us an idea of what the new cattle will be like.

ANNEXES

Appendix 1:

1- Do you have previous knowledge on how to carry out a correct selective breeding in determined periods of time?

to. Yeah.

b. No.

2- How appropriate do you consider selective breeding (human intervention in animal reproduction) to be?
to. Inappropriate
b. Regular
c. Appropriate
3- Do you use any zootechnical option that has the modern guarantee to increase animal performance?
to. Yeah
b. No
4- Would you like to increase your productivity, your resistance to the environment and to the diseases present in it, generating a better adaptation of your animal species?
to. Yeah
b. No
5- How good is the reproductive capacity of your cattle?
to. Bad
b. Normal
c. Well
6- How appropriate is the cattle care by the farmer?
to. Inappropriate
b. Regular
c. Appropriate
7- Do you have a technique for optimal feeding of your cattle?
to. Yeah
b. No
8- Do you have the pedigree record of your bovines?
to. Yeah
b. No
9- What breed of cattle do you have?
to. bost taurus
b. Gerefort
c. nelone
d. Others
10- Is the environmental climate suitable for the breeding and reproduction of bovine animals?
to. Yeah
b. No
11- Do you think that the weather greatly influences the quality of meat and milk at the time of processing?
to. Yeah
b. No

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