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An Overview of Artificial Neural Network and its Applications

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Abstract
This paper presents an overview of Artificial Neural Network (ANN). The study of neurons and its discrete representation by the set theory is the key objective of this paper. New data structure technique is proposed in this paper by using the mechanism of (ANN). The finite dimension of the field is generalized in this paper. The linear transformation and the representation of the vector basis are applied to propose the said structure.

Keywords: *ANN, Vector, Basis, Data, Linear Transformation, Set Theory.*

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INTRODUCTION

Akaike et al [1] presented an advancement and an application of information theory to design data interpretation technique in 1977. In 1993, there are three research papers [2-3] are published on physiological application. This paper presents the medical data and its transformation as the resultant of the survey of [4-12] over the Jordon canonical form into the artificial neural network as below;A function ø is defined on n-data of k-dimension of the matrix A.A standard basis is presented as below bythe function ø over the K_n field:

$$Ø: K^n \to K^n$$

Let N be a set of neural network defined as :

$$N = \{ n1, n_2, \ldots, n_m\}$$

Then , the function ø is defined as the linear transformation by

$$Ø: N \to N$$

Let the field be k. the finite dimensional vector space N is defined over K.

Let, the polynomial be q defined as the minimal polynomial over the ø – cyclic space.

Then,

$$q = n^r + a_{r-1}n^{r-1} + \ldots + a_0 \epsilon\ K\ \ n$$

Where , n is defined as the sequence of neural network as;

$$n = (n1, n_2, \ldots, n_m)$$

And r is defined as the dimension of the field k as:

$$r = \dim_k N$$

Hence, N has an ordered basis V relative to which the matrix of ø defined by:

$$A = \begin{bmatrix} O\ 1_k. & . & .0 \\ & .. & \\ & .\ 1_k & \\ -a_0 & -a_1 - a_{r-1} & \end{bmatrix}$$

The Representation

Then, the vector basis V is represented by;

$$[V = V, ø(v), ø^2(v), \ldots\ldots.., ø^{r-1}(v)]$$

Where, $v \in N$.

This matrix is called a companion matrix of the monic polynomial as ;

$$Q \in N [n]^2$$

Such that;

$$q = n + a_0$$

Then,

$$A = (-a_0)$$

By the neural network; Another neural function is defined as;

$$\psi : N \rightarrow N$$

This is a linear transformation of a finite dimensional vector space N over a field K.

Then, N is a ψ – cyclic space and ψ has a minimal polynomial:

$$q = (n-)^{r};$$
$$b \epsilon K;$$

If and only if;dim $_k$ E = r and N has an ordered basis relative to the function ψ over the matrix B:

$$\begin{bmatrix} b & 1_k & 0 . & . & . & 0 \\ 0 & b & 1_k . & . & . & \\ & . & & . & & \\ & . & & . & & \\ & . & & & 1_k & \\ 0 & . & & . & & 0_b \end{bmatrix}$$

The Proposed Data Structure

This r × r matrix B is called the elementary Jordan matrix associated with the neural network function over the medical data M.

Thus;

$$(n - b)^{r} \epsilon k [n]$$

Such that;

$$r=1B=(b)$$

$$R \times R \times .... \times R$$

If, R_1, R_2, ... , $R_n$and C be modules over the neural network set N;

$$N = \{ n_1 , n_2 , ..., n_m \}$$

There is an identity.

Then a function;

$$f : R \rightarrow R$$

Or

$$f : R_1 \times . . . \times R_n \rightarrow C$$

Is referred as R – multilinear represented by;

$$F\ (b1, \dots\dots\dots\ ,b_{i-1}\, rb\ +\ b_{i+1}, \dots\dots\ ,b_n$$

$$= rf\ (b_1, \dots, b_i - 1, b_{i+1}, \dots\dots, bn)$$
$$+\ \ sf\ (b_1, \dots, b_{i-1}, b\ , b_{i+1}, \dots\dots..b_n)$$

Where;

$$B \epsilon R$$

And;

$$B = \{b_1, b_2, ... ,b_n\}$$

Let,

$$C = R,$$

Then, the new networks for b as;

$$B_1,B_2, ...,B_n$$

Represented by;

$$B_1 = B_2 = ...= B_n = B$$

There are two linear neural network as b and N defined as bilinear.

So, $f : B^n \rightarrow N^{-n}$

The symmetric is defined as;

$$F(b_{61}, ..., b_{6n}) = f (b_1 , ... , b_n)$$

Thereis the permutation$\sigma \epsilon N$

The skew – symmetric is defined as;

$$F(b_{61}, ...,b_{6n}) = (sgn\ 6)\ f\ (b_1, ... ,b_n)$$

The alternate network is defined with the function;

$$F(b_1, ... ,b_n)= 0$$

Such that;

$$b1 = by;\ i \neq j$$

The elements of N is defined as the elements of matrix as;

$$N = \begin{bmatrix} a_{11} . \ . \ . \ . \ . a_{1n} \\ a_{m1} . \ . \ . \ . \ . a_{mn} \end{bmatrix}$$

Then the matrix d is defined as;

$$d: B \times B \rightarrow R$$

By

$$[(a_{11}, a_{12}), (a_{21}, a_{22})] \rightarrow a_{11}a_{12} \rightarrow a_{12}a_{21}$$

Generalizing as;

$$[(a_{11}, a_{12}, a_{13}, (a_{31}, a_{32}, a_{33} \rightarrow a_{11}a_{12}a_{13}a_{31}a_{32}a_{33}]$$

For n × n matrices also with the distance determinant function f.

By slow – symmetric of the network with the medical data over the determinant function is defined by;

0 =Thusf $(b_1 + b_2, b_1 + b_2)$
$=f(b_1, b_1) + f(b_1 + b_2) + \ldots$ ff (b_2, b_2)
$= 0 + f\,f(b_1, b_2) + f(b_2, b_1) + 0$

Then,

$$(R^n)^n = R^n \oplus \ldots \oplus R^n \text{and}$$

$$(B^n)^n = B^n \oplus \ldots \oplus B^n$$

Thus,

$$(R^n)^n \rightarrow R$$

$$(B^n)^n \rightarrow R$$

The efficient network is function with the R – Multi linear and B – Multi Linear by the followings;

$$F: (R^n)^n \rightarrow R$$

And

$$F: (B^n)^n \rightarrow R$$

Such That;

$$F(n_1, n_2, \ldots, n_m) = r$$

Where$(n_1, n_2, n_3 \ldots, n_m)$ is referred as the basis of the network N.

The error – corretor is set with the new set X;

$$X = \{X_1, X_2, \ldots, X_n\}$$

$$X \rightarrow A$$

By

$$X_1 \rightarrow A$$

$$X_2 \rightarrow A$$

$$Xn \rightarrow A$$

The standard basis is;

$$\{e_1, \ldots, e_n\}$$

Then,

$$(e_i \ldots, e_n) \rightarrow 1_n$$

Thus, the uniqueness of the network is presented as;

$$(X1, \ldots, Xn) \in (R^n)^n$$

And

$$(X_1, \ldots, X_n) \in (B^n)^n$$

By Bilinear;

$(X1, \ldots, Xn) \in f: (R^n)^n$ $(B^n)^n$

So,

$$X_i = (a_{i1}, \ldots a_{in})$$
$$= = \sum_{j=1}^{n} a_{ij}e_j$$

By isomorphic property;

$$(R^n)^n \cong f_n R(X_1, \ldots, X_n)$$

And

$$(B^n)^n \cong f_n R(X_1, \ldots, X_n)$$

Then

$$(R^n)^n \rightarrow a_{ij}$$

$$(B^n)^n \rightarrow a_{ij}$$

By multilinearity ;

$F(x1, \ldots, Xn) = f((x + a)^n = \sum_{y1} a_{1y1}\, e_{y1}, \sum_{y2} a_{2y2}\, e_{y2}, \ldots, \sum_{yn} a_{nyn}\, e_{yn})$
$= \sum_{j1} \sum_{j2} \ldots \sum_{jn} a_1y_1, a_2y_2 \ldots a_ny_n\, f(e_{y1}, \ldots e_{yn})$

Hence,

$F(N_1, N_2, \ldots\ldots, N_m) = \sum_{i=1} \sum_{y=1} a_{iy} n_{iy}$

This,
$F(X_1, X_2, \ldots\ldots X_n) = 0$
$F(B_1, B_2, \ldots\ldots B_n) = 0$
$F(N_1, N_2, \ldots\ldots N_n) = 0$
if $(E_1, E_2, \ldots\ldots E_n) \rightarrow In$

Hence

$$f : R_n \rightarrow R_n \rightarrow N$$

CONCLUSION

This data structure comprises with the finite mapping thus provides the semantic security. The medical data contains the multilinearity property thus by isomorphic mapping the data transforms into information in multi-layer basis.

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