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AN EFFICIENT KINSHIP VERIFICATION AND FAMILY TREE CONSTRUCTION FRAMEWORK USING GRAPHICAL LEARNING AND KNOWLEDGE REPRESENTATION

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Abstract

Kinship verification and identification from image data has been a challenging and complex field in computer vision over the last two decades. It determines the blood relation between two people from their facial images. It has numerous applications, including finding missing children, forensic research, and is also used in genealogical research and the reconstruction of family history. This paper presents a novel approach for automatically creating family trees from a set of family pictures up to three levels. Traditional methods rely on manual research and rule-based systems, which can be time-consuming and prone to errors. The proposed approach is a hybrid solution that combines the strengths of graphical neural networks with the accuracy of mathematical logic. First, the GCN technique was applied to learn an underlying representation of individuals from their facial features and identify undirected kin relations. These relationships are then expressed using first-order predicate logic to determine directionality and construct a comprehensive family tree. Creating a family tree plays a vital role in establishing individual identity by linking each person to their family members. This effort directly supports Sustainable Development Goal (SDG) 16.9, which aims to provide legal identity for all. We demonstrate our approach on the FIW dataset, and the results show that our approach works efficiently and has improved accuracy compared to traditional methods.

Keywords: GCN, RGCN, Kinship verification, predicate logic, family tree, SDG16.9

1. Introduction

Kinship verification is a challenging task in computer vision. It has numerous applications in computer vision, as well as in the real world. It is used to manage family albums, analyze social media, locate missing children and parents, as well as for recognition and face verification in computer vision[1]. Most studies focus on analyzing kinship in pairwise face images independently, aiming to verify whether a face pair has a kinship relation or not. However, these studies yield unidirectional results, and the roles of the faces are not defined.

Our approach utilizes a graph convolutional network (GCN) technique to identify and catalog minor visual attributes that represent family relationships. After obtaining kin relations,

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a set of relational logic and theory-based logical deduction rules is used to arrange these relationships into a logical family tree structure.

This work builds upon our previous study[2], in which a Relational Graph Convolutional Network (RGCN)-based framework was employed for kinship verification between pairs of facial images. In this paper, we extend that approach to handle multiple faces simultaneously by modeling the relational structure of family members in a graph and inferring directionality using logical reasoning, without relying on age or gender cues. Recognizing kinship among multiple faces is more challenging, as it involves reasoning about numerous relationships simultaneously. A single face may share different kinship roles with various others, and multiple face pairs may correspond to the same relationship type. This paper focuses on a three-generation family, as it is the most standard social group for kinship analysis. The goal of this paper is to perform kinship identification using a single picture of a three-generation family or individual pictures and generate a corresponding family tree that clearly shows the roles and precise relationships of all family members.

The approach begins with a binary classification GCN model, followed by the RGCN model, after obtaining the kin relation between all pairs of images. Logical deduction is applied to identify the correct role of all pictures. The basic architecture of the proposed approach is shown in Figure 1.

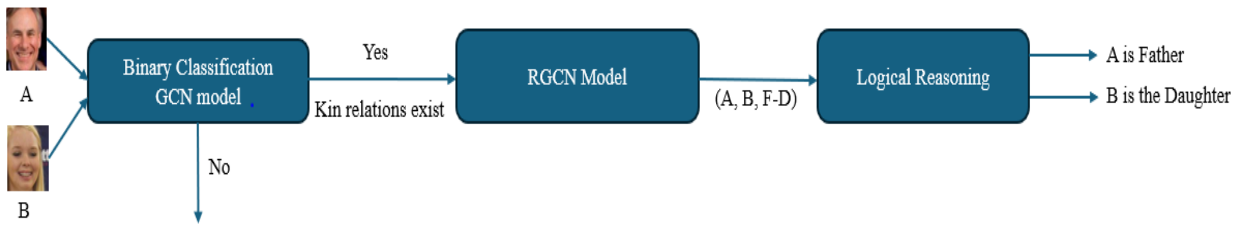

Fig 1. Process of Proposed Approach

The development of this model and its family tree construction facilitates the verification of familial relationships in forensic and humanitarian settings. Consequently, this study aligns with and supports United Nations Sustainable Development Goal (SDG) 16.9, which seeks to provide universal legal identity, including birth registration.

This paper contributes to the growing field of computational genealogy by providing a robust framework for kinship verification and family tree construction. It offers insights into the development of automated tools for historical and genealogical research. Through this interdisciplinary approach, this paper paves the way for future advancements in understanding and visualizing familial relationships, enriching the exploration of our ancestral past.

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1.1 Key contributions of this study

- The existing work is based on age and gender differentiation, which has constraints for appropriate model selection and implementation. Continuing with our proposed work, it is based on knowledge representation-oriented mathematical logics.
- Some of the work is based on a two-level hierarchy (parents and their children), but our novel approach emphasizes three three-level hierarchy (Grandparents, parents, and their children).
- Graphical neural networks and knowledge representation provide better results in comparison to traditional neural network approaches.

1.1.2 Advantages of logical reasoning

To determine direction in kinship relations, for example, identifying who is the parent and who is the child in a predicted father–son relationship, one common approach is to estimate the age and gender of each individual and, based on these estimates, determine who is the parent and who is the child. However, this method has significant limitations: age and gender predictions can be noisy, culturally biased, and unreliable across varying image conditions or demographic groups. To overcome these challenges, we adopt a logic-based approach that relies on structural reasoning rather than individual demographic features. By using propositional logic and relational consistency rules, we infer directionality based on the overall pattern of relationships within the family graph. This method ensures biologically valid hierarchies (e.g., no individual has multiple biological fathers or cycles in lineage), enables inference of complex relations like grandparent or sibling, and avoids dependence on sensitive or error-prone demographic estimation. As a result, our logic-based framework offers greater interpretability, robustness, and ethical soundness, making it a more effective and generalizable solution for kinship reasoning across diverse datasets.

2. Literature Review:

Studies on automatic kinship verification began in 2010. Early approaches primarily relied on handcrafted features and classical machine learning algorithms[3][4][5]. Fang et al. [3] attempted to identify kin relations from shallow features such as facial geometry, eye color, or lip size. Goyal A. et al. [5] extracted subparts such as the left eye and right eye, and used them for matching. In a few studies[6][6], [7][7][8], traditional feature extraction techniques such as LBP, HOG, SIFT, LDP, BSIF, and matched these features for verifying the kin relation. Kohli et al. [9] applied the difference of Gaussians (DoG) to facial parts, and based on matching, they concluded whether there was a relation or not. Yan et al [10] used 68 facial landmarks to judge the kinship relation between image pairs. Lu et al. [11] introduced the metric learning approach. After 2015, deep learning was applied for kinship verification [11][12][13][14][15]. Song and Yan et al. [9] addressed the problem that available kinship data sets are very small, and the model can't be trained with these small data sets. They proposed a data augmentation technique for the kinship dataset in which they augmented data from the attribute level rather than authentic facial images. To improve the accuracy of different gender cases, such as Father-

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Daughter or Mother-Son, Feng et al.[10] proposed Gender-FEIT, in which they designed a GAN network and trained it with face representations of different genders, allowing the model to learn the invariance of other genders. Li, L [16] and Nandy [17] utilized a Siamese network, while D. Jeyashaju et al. [18] extended this model and proposed a three-level subnet of the Siamese network. Fibriani et al. [19] combined the vision transform with the Siamese network.

Many studies focus on kinship verification, but only two studies [15] [20] have explored the creation of a family tree from kin relations; however, in both studies, a gender and age prediction model was used, and a family tree was constructed for only two-level (parents-child) relations..

3. Methodology

This paper proposed a novel approach for creating a family tree from a given set of images. It's a three-step approach, in the first step, a 3-layer GCN model was used for binary classification, if the image pair has kin relation, then in second step RGCN model is used to find which type of kin relation exist, after finding kin relation between all pairs, in third step predicate logics are used to find which image is playing with role. The process flow of the proposed approach is described in Figure 2.

Input *A Group family photograph or an individual picture of all family members*

Step1: *If the number of pictures == 1*

Extract an individual face image from the picture and assign a temporary name to all images.

Step2: *Finding the relation between the pictures*

Using the GCN and RGCN models, we get the relation between every pair of images. It returns a list of undirected relationships between individuals, where each relationship is known (e.g., father-son, mother-daughter) but without specifying which individual holds which role.

Step3: *Collect Relationship Data*

Gather all relationships into a set R of tuples (a, b, type), where a and b are individuals, and "type" is the relationship type (e.g., parent-child) without indicating the direction.

Step4: *Infer Generational Levels*

Apply heuristic reasoning concepts to find direction in relations.

Output *A probable family tree that respects the generational hierarchy inferred from the relationships.*

Fig. 2 Process Flow of the proposed approach

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Algorithm 1: Kinship Verification using GCN and Knowledge Representation

Input: A set of pictures $\mathcal{P} = \{p_1, p_2, ..., p_n\}$ (a set of n pictures, either one or a group picture)

Output: Labeled relations and $\mathscr{L}$-levels $\mathcal{G}_r = (\boldsymbol{\mathcal{F}}, \mathscr{E})$ of a directed graph

START

If $|\mathcal{P}| = 1$ then
Define the face set $\boldsymbol{\mathcal{F}} = \{f_1, f_2, ...f_m\}$ from p_1
Assign a temporary ID: for each $f_i \in \boldsymbol{\mathcal{F}}$, we have $ID(f_i) \leftarrow t_i$
Else
For every $p_i \in \mathcal{P}$, take the face $f_i \rightarrow \boldsymbol{\mathcal{F}} \leftarrow \{f_1, ..., f_n\}$
End if
Let the undirected set of relations $\mathscr{R} \leftarrow \emptyset$
For any $i \neq j$, $\forall$ (f_i, f_j):
$r_{ij} = \mathcal{G}(f_i, f_j)$ //, $\mathcal{G}$ is GCN/RGCN model: $\mathcal{G}$: $\boldsymbol{\mathcal{F}} \times \boldsymbol{\mathcal{F}} \rightarrow$ {relation types}
$\mathscr{R} \leftarrow \mathscr{R} \cup \{(f_i, f_j, r_{ij})\}$
End for
Initialize a directed graph $\mathcal{G}_r \leftarrow (\mathcal{V}, \mathscr{E})$, where $\mathcal{V} = \boldsymbol{\mathcal{F}}$, and $\mathscr{E} = \emptyset$
For each $(f_i, f_j, r_{ij}) \in \mathscr{R}$:
If direction(r_{ij}) unknown:
Derive dir_{ij} with heuristic rule $\mathscr{H}$: $\mathscr{H}(f_i, f_j, r_{ij}) \rightarrow (f_i \rightarrow f_j)$ or $(f_j \rightarrow f_i)$
$\mathscr{E} \leftarrow \mathscr{E} \cup$ {directed edge which follows from dir_{ij}}
End for
Let $\boldsymbol{\mathcal{F}} \rightarrow \mathbb{Z}$ (e.g., parent > child) be a definition of the generational level function $\mathscr{L}$.
Traverse $\mathcal{G}_r$ by BFS or topological sort and label $\cup\mathscr{L}(f_i)$

END

3.1 Graphical Convolution Model

This proposed work used two graphical neural networks to identify kin relations; The first one is designed for binary classification, specifically to perform kinship verification on a graph. It operates in two main stages. First, an encoder takes the features of individual people (nodes) and their existing connections as input. This encoder intelligently aggregates information from neighboring nodes through a process called "message passing," effectively learning person

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embeddings that represent each individual's unique attributes and their relational context within the familial graph. These learned person embeddings then serve as the input for the second stage: the kinship predictor. This component takes pairs of generated person embeddings, combines them, passes them through a linear layer, and outputs a single score. This score represents the likelihood of a family relationship existing between the two corresponding individuals. Finally, a sigmoid activation function converts this raw score into a probability, which is then used to produce a binary classification: either a kinship exists ("YES") or it does not ("NO") between two individuals.

Suppose a kinship relation is determined between a pair of individuals. In that case, our proposed 4-layer RGCN model [2] was used to predict the exact relation between the image pair. That model was trained on a weighted combined loss function that integrates ArcFace loss and Center loss to effectively classify the specific type of kinship.

3.2 Logical reasoning

After determining that the pair has a kin relation, it is necessary to decide which person plays which role. For that, predicate logic and logical reasoning were used in this approach. The family reasoning concepts say that if two people in a family have no kin relation, they are either spouses or in-laws. Similarly, if two people have the same biological parents, they are siblings. We explain all the reasoning in the following five cases.

Given a set I of individuals and a relation $R \subseteq I \times I \times T$, where T denotes the set of relationship types, we define the following cases:

Case 1: parents-children relationship

$\forall(a,b,c) \in I \times I \times I$, (a, c, "F-S") ∧ (b, c, "M-S") ⟹ a is the father, b is the mother, and c is the child. and a and b have no kin relation. They are husband and wife.

Case 2: Father with Multiple Children

$\forall(a,b,c) \in I \times I \times I$, (a, b, "FS/FD") ∧ (a, c, "FS/FD") ⟹ a is Father, and (b, c) are "siblings".

Case 3: Parent-Child with Grandparent-Grandchild Inference

$\forall(a,b,c) \in I \times I \times I$, (a,b,"father-son") ∧ (b, c, "father-son") ∧ (a, c, "GF-GS") ⟹ b is Father.

or

$\forall(a, b, c) \in I \times I \times I$, (a, b, "Mother-son") ∧ (b, c, "father-son") ∧ (a, c, "GM-GS") ⟹ b is Father.

Case 4: Sibling Relationships (Brothers or Brother-Sister)

$\forall(a, b) \in I \times I$, (a, b, "BB/SS") ⟹ a and b are siblings

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Case 5: Grandfather with Multiple Grandchildren

$\forall$(a, b, c)$\in$I×I×I, (a, b, "GF-GS/GD") $\wedge$ (a, c, "GF-GS/GD") $\Longrightarrow$ a is Grand Father, and b, c are siblings.

Case 6: Grandmother with Multiple Grandchildren

$\forall$(a, b, c)$\in$I×I×I, (a, b, "GM-GS/GD") $\wedge$ (a, c, "GM-GS/GD") $\Longrightarrow$ a is Grandmother, and "sibling" (b, c)

4. Result

The proposed approach was evaluated on the FIW (Families in the Wild) dataset, which includes images labeled with eleven distinct kinship relations. For binary classification, the focus was on determining whether a kinship relation exists between a given pair of individuals or not. To provide input to the GCN, the graph representation of the dataset was constructed, where each node corresponds to a unique image and edges represent known kinship relations between the associated individuals. The binary classification model achieved an accuracy of 98%, demonstrating the effectiveness of the proposed approach. Accuracy and loss graphs are shown in Figure 3.

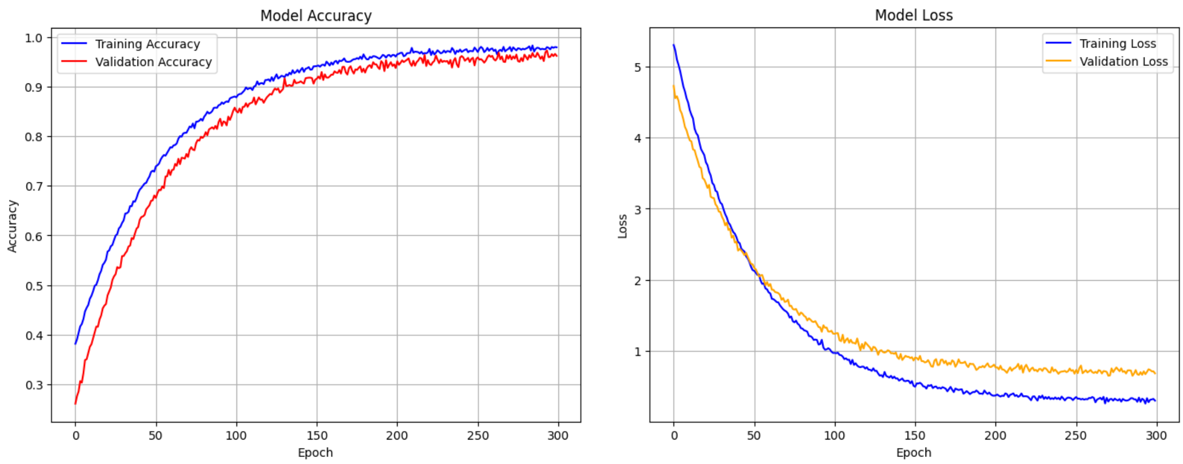

Fig 3. Accuracy and Loss graph of the binary classification model

Figure 4 illustrates the output at each stage of the proposed framework. Work starts with images of seven family members, as shown in Fig. 4(a). In the first step, all possible pairs (21 combinations) of these images are processed using a binary kinship classification model, with the results presented in Fig. 4(b). Among the 21 pairs, four are identified as non-kin, leaving 17 valid kinship pairs for further processing. These 17 pairs are then passed through the RGCN model, which predicts the specific kinship relations between each pair, as depicted in Fig. 4(c). Subsequently, in the next step, predicate logic was applied to the RGCN output to infer directional roles for each individual (e.g., parent or child) based on relational consistency and constraints, as shown in Fig. 4(d). Finally, Fig. 4(e) presents the reconstructed family tree, representing the inferred structure and relationships among all family members.

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I1 I2 I3 I4 I5 I6 I7

(a) Faces of all family members

I1 and I2 has Kin relation
I1 and I3 has Kin relation
I1 and I4 has Kin relation
I1 and I5 No Kin relation
I1 and I6 has Kin relation
I1 and I7 has Kin relation
I2 and I3 No Kin relation
I2 and I4 has Kin relation
I2 and I5 No Kin relation
I2 and I6 has Kin relation
I2 and I7 has Kin relation
I3 and I4 has Kin relation
I3 and I5 No Kin relation
I3 and I6 has Kin relation
I3 and I7 has Kin relation
I4 and I5 has Kin relation
I4 and I6 has Kin relation
I4 and I7 has Kin relation
I5 and I6 has Kin relation
I5 and I7 has Kin relation
I6 and I7 has Kin relation

(b) Out of the binary Classification Model

I1 and I2 FS
I1 and I3 MS
I1 and I4 FD
I1 and I6 FS
I1 and I7 FS
I2 and I4 GFGD
I2 and I6 GFGS
I2 and I7 GFGS
I3 and I4 GMGD
I3 and I6 GMGS
I3 and I7 GMGS
I4 and I5 MD
I4 and I6 Sibs
I4 and I7 Sibs
I5 and I6 MS
I5 and I7 MS
I6 and I7 BB

(c) Output of RGCN Model

I1 and I2 FS
I1 and I3 MS
Conclusion : I2 is Father, I3 is Mother, and I1 is Son

I1 and I4 FD
I1 and I6 FS
I1 and I7 FS
Conclusion: I1 is Father, I4 Daughter, I6 is Son, I7 is Son

I2 and I4 GFGD
I2 and I6 GFGS
I2 and I7 GFGS
Conclusion: I2 is Grand-Father, I4 is Grand-Daughter, I6 is Grand-Son, I7 is Grand-Son

I3 and I4 GMGD
I3 and I6 GMGS
I3 and I7 GMGS
Conclusion: I3 is Grand-Mother, I4 is Grand-Daughter, I6 is Grand-Son, I7 is Grand-Son

I4 and I5 MD
I5 and I6 MS
I5 and I7 MS
Conclusion: I5 is Mother, I4 Daughter, I6 is Son, I7 is Son,

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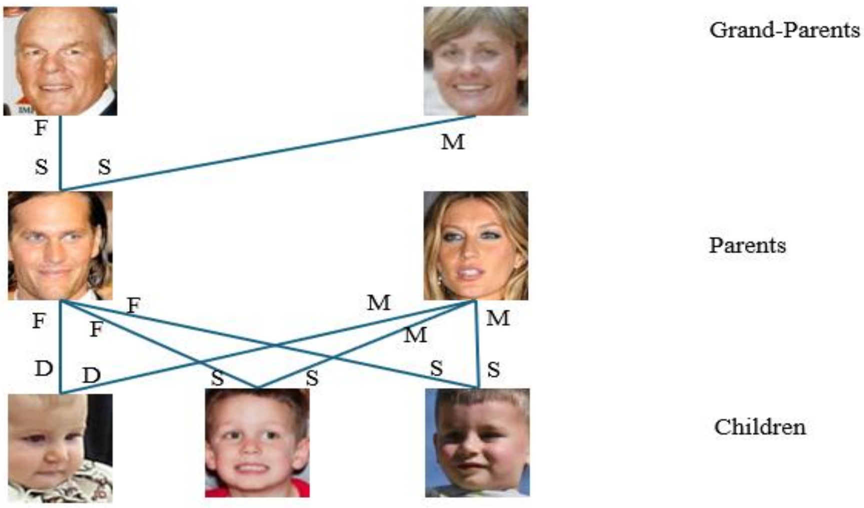
I2 and I4 GFGD
I1 and I2 FS
I1 and I4 FD
Conclusion: I2 is Grand-Father, I1 is Father, I4 Grand-Daughter

I3 and I6 GMGS
I1 and I3 MS
I1 and I6 FS
Conclusion: I3 is Grand-Mother, I1 is Father, I6 is Grand-Son

I4 and I6 Sibs
I4 and I7 Sibs
I6 and I7 BB
Conclusion: I4, I6 sister brother, I4, I7 Sister Brother, I6,I7 Brother, Brother

(d) Output of logical reasoning



(e) Family Tree

Fig 4. Step-by-step output of the proposed approach

5. Conclusion

In this paper, we utilize a graphical neural network for kinship verification and a novel logic-based framework for inferring kinship direction without relying on age or gender estimation. Our approach leverages relational consistency and logical constraints to determine the correct direction of relationships across multiple individuals. This framework not only improves robustness and generalizability but also introduces a more ethical and scalable solution to multi-face kinship analysis.

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